Essays in Information Economics

by

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For my parents, my brothers and my sister

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CHAPTER I

Introduction

1.1 Overview

The Internet has facilitated almost costless communication, and easy access to copyrighted works worldwide. Legal enforcement has experienced limitations such that senders can email millions of recipients anonymously, and users can pirate copyrighted works without legal punishment. What are the economic responses to such challenges? In this dissertation, I study two such responses: anti-spam mechanisms and open contents.

I derive conditions under which distribution and care level taken to avoid damages in open contents are socially efficient or inefficient. Then I report experimental results on the production of open contents. I compare free-riding, efficiency and spillover when there are large or small teams using non-modular or modular production. Lastly, I propose and evaluate an anti-spam mechanism I call an uncensored communication channel, with the aim of enticing spam-demanders and spam-suppliers to trade in there instead of the traditional email channels.

In this dissertation, there are five chapters:

Chapter I: Introduction

Chapter II: A Tort Model of Open Contents

Chapter III: Modularity and Team Size in Open Content Experiments

Chapter IV[1]: Using Uncensored Communication Channels to Divert Spam Traffic

Chapter V: Conclusions

1.2 Scope

1.2.1 Open Contents

Contents, such as software, music, films or books, are defined here to be open if one is free to use, reuse, and redistribute them[2]. In this dissertation, I use a tort model to investigate if the individually optimal levels of redistribution and care taken to avoid monetary losses in open contents are different from the socially optimal levels. I also run an experiment to investigate if the modularity principle, prevalent in open source production, can increase efficiency and spillover and reduce free-riding when team size varies.

1.2.2 Spam

I limit consideration to spam defined as *bulk, unsolicited, commercial email*; that is, effectively identical (but usually randomly disguised) messages sent unsolicited to large numbers of recipients with the goal of inducing a willing, mutually-beneficial purchase by the recipients. With this definition (I will call it "spam" for convenience, but it's merely one subspecies), I rule out malicious bulk unsolicited email (e.g., email carrying a virus payload); I rule out deceptive email (e.g., "phishing" messages that attempt to trick recipients into revealing valuable personal information such as bank passwords); and I rule out email (though initially unsolicited) sent to a mailing list,

[1] Jeffrey MacKie-Mason is my coauthor. I would like to thank him for giving me the permission to use this paper as part of my dissertation.

[2] This is from the Open Knowledge Definition website, which claims this to be the simplest version of their more complete definition available at: http://www.opendefinition.org/, accessed December 15, 2009. Other definitions exist, for example, see *Newmarch* (2000) and *Liang* (2004). There are a few related concepts such as user-generated contents (*Krumm et al.* (2008)), open innovation (*Chesbrough* (2004)), user innovation (*Von Hippel and Von Krogh* (2003)) and the like. A comparison between these concepts is outside the scope of this research.

from which one could unsubscribe. What I rule out is not insignificant; I just take this definition as a starting point and leave the study of other email problems for future research. I do document that commercial spam is the most prevalent form. And I have analyzed how the results change when the proportion of malicious and deceptive email changes.

Defined as what I have done, spam is an instance of a differently-named, well-known phenomenon: advertising. Using the less-pejorative moniker “email advertising” might give us a good start on a thoughtful, systematic consideration; certainly, it might help us recognize that at least this type of spam is not per se evil or morally deficient (though, as with any advertising, some population subgroups might conclude that the products advertised might fail that group’s morality test). Nonetheless, I will use “commercial spam” or just “spam” for short, because I relish the powerful affective response the term receives, and the opportunity to puncture the pejorative bubble it engenders.

In this dissertation, I propose and evaluate an anti-spam mechanism called uncensored (open) communication channels. Such channels may contribute to a reduction in the flow of spam, and at the same time give advertisers a reason to *increase* the informative content and quality of their ads, to the benefit of those who *do* want to buy goods.

1.3 Extended Abstracts

1.3.1 Chapter II. A Tort Model of Open Contents

The delineation of rights in open contents seems quite unclear to many stakeholders. There is seldom dedicated staff to verify possible intellectual property infringements for contributions made by volunteers worldwide. For some open contents such as Wikipedia and open source software, the production involves many amateur innovators whose contributions could decrease when faced with liability for certain damages. Such damages are largely confined here to those related to copyright actual damages and profits[3,4]. Although open contents are supposed to be free to use and re-distribute, there are liability implications. For example, the current innovator might not know that the existing work already contains proprietary materials. Vendors who redistribute or add value to open contents, and users who consume the product could be liable if the innovator includes copyright infringing works.

The major research question is: Given a liability rule, are the individually optimal levels of redistribution and care taken to avoid damages in open contents different from the social optimal levels?

I use a model similar to those in the torts literature (*Landes and Posner* (1985), *Landes and Posner* (1987), *Miceli* (1997), and *Shavell* (1980)) to study the inclusion of value-adding resellers (vendors) who do not need to pay the original sellers (innovators) for production. I model after the SCO-Linux controversy to include an agent who receives a positive expected payment in intellectual property lawsuits but it is hard for other agents to contract with this agent ex ante. I then analyze how the litigation between this agent, vendors, innovators and users affects care levels and quantities distributed.

Some main results here confirm with the standard results that in general efficiency requires the lowest cost agents to engage in activity until their marginal costs equal to that of other agents. And it is well known in the literature (*Coase* (1960)) that when

[3]The owner whose copyright has been infringed can choose between two mutually exclusive choices of damages: i) actual damages and profits ii) statutory damages.

The primary measure of recovery of actual damages is based upon the loss of market value of the copyrighted work due the infringement. Alternatively, the plaintiff could show the defendant's profits from sales of the infringing works.

Statutory damages are outside the scope of this paper because the calculation of such damages greatly increases the complexity of the model. For example, according to the the statute, the damage shall not be less than $750 nor more than $30,000 per work infringed. This range will be changed depending on whether the infringement is committed willfully.

[4]Some but not all features of the current analysis apply to other intellectual property infringements related to patents or other damages related to product failures. These are, however, outside the scope of this paper.

transaction costs are zero, liability rules are irrelevant and thus care and redistribution will be socially efficient. But since transaction costs are not zero in reality, the main contributions here are the derivations of some necessary conditions for efficiency and sufficient conditions for inefficiency in the context of open contents.

For efficient quantities, it is necessary for the vendors to bear more liability than the innovator when the marginal spillover effect and the innovator's care costs of the marginal copy are high relative to the vendor's care costs of the marginal copy. For efficient care, it is necessary for care levels to obey the implicit analytical forms of the optimal liability shares I have derived.

For inefficient care, I have derived some sufficient conditions related to the interaction of liability shares and litigation costs. For example, in the no liability to users case, efficient care levels cannot be obtained if the litigation costs are too high. In the no liability to the innovators and vendors case commonly used in open content licenses, efficient care levels cannot be achieved if there are non-zero litigation costs.

1.3.2 Chapter III. Modularity and Team Size in Open Content Experiments

The open source movement has already challenged the biggest players in the computer science industry. Attempts have been made to broaden the scope to areas other than software. This chapter focuses on one of these areas called open contents. How to ensure success in such area using the open source concept? Should principles prevalent in coding be also applied to contents? One principle I mainly investigate here is modularity with different team sizes.

Modularity is deeply rooted in the computer science literature[5]. The concept of information hiding, pioneered by *Parnas* (1972), says that non-modularity is not optimal if the inner workings of a module overlap with the responsibility of another

[5] *Simon* (1962) and *Alexander* (1964) are some of the earliest works.

module. For instance, non-modularity implies that errors are serially correlated across modules. Various experimental studies (e.g. see *Camerer* (2003) pp. 383 for a review) show that it is easier to achieve a socially inefficient outcomes (even though more socially efficient outcomes are also Nash) as team size increases when non-modularity takes the form of minimum effort games[6,7]. All these are consistent with the following theories in the open source context. *Baldwin and Clark* (2006) (pp. 1126) show theoretically that social efficiency decreases because non-modularity leads to a higher free-riding level among open source developers. Varying team size and modularity, *Johnson* (2002) (pp. 658) shows theoretically that non-modularity is socially inefficient (due to free-riding) only for large teams of developers.

However, both *Baldwin and Clark* (2006) and *Johnson* (2002) assume that the costs of development are independent across individuals, implying that the spillover of know-how does not matter in cost saving. This assumption is perhaps a key deviation from the essential features of open contents. Open contents are free to use, reuse, and redistribute. This allows individuals to share and redistribute with each other, without costs, code or methods used. This paper relaxes the cost independence assumption by allowing some spillover of know-hows.

I have not directly investigated whether and how open contents facilitate learning. But the data showed that spillover was significantly higher in the non-modular production. More, this experiment documents a case in which price was at times not used to coordinate resources in open contents where production was decentralized. Free-riding, measured as zero price to helpers, was prevalent in the experiment. Large teams were associated with a higher free-riding level than small teams, and free-riding was more severe when large teams work in a non-modular production environment.

[6]A minimum game takes this form. Individual i chooses an effort level from the set of non-negative integers to maximize his payoff determined by the minimum of the effort levels of all team members: $\text{Payoff}_i = \min_{i=1 \text{ to } N}\{\text{effort}_i\} - \text{cost}_i \times \text{effort}_i$. There are multiple equilibria in this game. *Anderson et al.* (2001) offers a review of the experimental results and plausible theories.

[7]This is a particularly important class of games (*Camerer* (2003), pp.376-7).

Free-riding resulted in the removal of a signaling function of price for the difficulty levels of tasks. However, this removal was not sufficient to lead to the catastrophic outcome of zero payoff. In fact, for one measure of efficiency, small teams were more efficient than large teams in the non-modular production and efficiency was higher in the modular production irrespective of team size. If the two team size levels here are a reasonable approximation to the team size levels in a given firm, here are some implications for managers concerning efficiency: if the production function is restricted to be non-modular, reduce the team size; with no such restriction, always choose the modular production function.

1.3.3 Chapter IV. Using Uncensored Communication Channels to Divert Spam Traffic

I offer a microeconomic model of the two-sided market for the dominant form of spam: bulk, unsolicited, and commercial advertising email. Most most spam is advertising, and thus should be modeled as a problem in the market supply and demand for advertising, rather than the usual approach of modeling spam as pure social cost to be eliminated. I adopt an incentive-centered design approach to develop a simple, feasible improvement to the current email system using an uncensored (open) communication channel. Such a channel could be an email folder or account, to which properly tagged commercial solicitations are routed without any blocking or filtering along the way.

Some proposals based on economic incentives have been gaining attention. These share an important feature with our approach to the problem: they typically are based on a presumption that users have heterogeneous values for receiving various email messages. In an experimental investigation of email stamps as a price for obtaining a recipient's attention, *Kraut et al.* (2005) found that charging causes senders to be more selective and to send fewer messages. This method, however, requires non-spammers to pay a price as well. *van Zandt* (2004) examines the design of an optimal tax that minimizes exploitation of attention through information overload. *Loder et al.* (2006) propose an attention-bond mechanism in which a sender deposits a monetary bond to a third-party agent, to be released only if the receiver tells the agent to do so. Payment systems require substantial infrastructure for full implementation. The infrastructure necessary for widespread micropayment is lacking, and for successful adoption into a service exhibiting network effects, such as email, it is likely necessary that there be early widespread, not incremental, adoption, which is difficult to socially engineer. Also, there is a norm of free email service. Legitimate senders may resist paying for outgoing email more strenuously than is strictly justified if they took into account the system benefits to their recipients.

Technical filters and legal rules raise the cost of delivering spam to readers. Costs are borne by spammers (who must develop ever-changing techniques for avoiding filters, etc.), but also by recipients, who spend time doing the difficult filtering and reviewing that cannot be automated, and paying higher costs for goods to cover the marketing expenses. On the other hand, an equivalent reduction in the benefits of spamming (e.g. by moving out spam demanders) should have the same incentive effect.

In this research, I characterize the *circumstances* under which spammers would voluntarily move much of their spam into the open channel, leaving the traditional email channel dominated by person-to-person, non-spam mail. This is the only symmetric pure-strategy Nash equilibrium besides the status quo. I show that under *certain conditions* all email recipients are better off when an open channel is introduced. Only recipients wanting spam will use the open channel enjoying the less disguised messages and cheaper sale prices, and for all recipients the dissatisfaction associated with both undesirable mail received and desirable mail filtered out decreases.

CHAPTER II

A Tort Model of Open Contents

2.1 Introduction

Contents, such as software, music, films or books, are defined here to be open if one is free to use, reuse, and redistribute them[1]. The delineation of rights in open contents seems quite unclear to many stakeholders. There is seldom dedicated staff to verify possible intellectual property infringements for contributions made by volunteers worldwide. For some open contents such as Wikipedia and open source software, the production involves many amateur innovators whose contributions could decrease when faced with liability for certain damages. Such damages are largely confined here to those related to copyright actual damages and profits[2,3]. For example, the

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[2] The owner whose copyright has been infringed can choose between two mutually exclusive choices of damages: i) actual damages and profits ii) statutory damages.

The primary measure of recovery of actual damages is based upon the loss of market value of the copyrighted work due to the infringement. Alternatively, the plaintiff could show the defendant's profits from sales of the infringing works.

Statutory damages are outside the scope of this paper because the calculation of such damages greatly increases the complexity of the model. For example, according to the statute, the damage shall not be less than $750 nor more than $30,000 per work infringed. This range will be changed depending on whether the infringement is committed willfully.

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current innovator might not know that the existing work already contains proprietary materials. Vendors who redistribute or add value to open contents, and users who consume the product could be liable as well.

The major research question in this paper is: Given a liability rule, are the individually optimal levels of redistribution and care taken to avoid damages in open contents different from the social optimal levels?

It is well known in the literature (*Coase* (1960)) that when transaction costs are zero, liability rules are irrelevant and thus care and redistribution will be socially efficient. But transaction costs are not zero in reality. I have derived some necessary conditions for social efficiency and some sufficient conditions for social inefficiency.

The next section presents some copyright infringement risks and measures to avoid them. Section 3 uses injurer-victim tort models to derive some optimal liability and bargaining arrangements across agents to deal with such risks. The last section concludes.

2.2 Copyright Infringements

The theory in the next section is about some strategic interactions of the users, innovators, and vendors of open contents. As a motivation, I present in this section the SCO-Linux controversy that highlights some copyright infringement risks and measures to avoid them.

SCO has claimed itself to be the "owner of UNIX" through a chain of sales. In 2003, SCO claimed that there had been misappropriation of its UNIX System V code into Linux. SCO has claimed that there is copyright infringing code in Linux[4]. SCO began numerous legal claims and threats against many vendors (e.g. IBM, Hewlett-Packard, Microsoft, Novell, Silicon Graphics, Sun Microsystems and Red Hat) and

the scope of this paper.

[4]See *SCO Group, Inc.* v. *Novell, Inc.*, 578 F.3d 1201 (10th Cir. Utah 2009).

end users[5]. However, on August 10, 2007 Judge Dale Kimball, hearing the *SCO* v. *Novell* case, ruled that "...the court concludes that Novell is the owner of the UNIX and UnixWare Copyrights"[6]. In September 2007, SCO filed for Chapter 11 bankruptcy protection.

Although SCO's claims so far have not been upheld by the courts and the legal impact on both Linux and Unix seems minimal, this episode highlights the possibility that the transaction costs involved in clearing copyrights in open contents ex post is non-trivial. This points to a demand to clarify such rights ex ante. Vendors could assist such clarifications especially when there are more profit motives (e.g. spillover effects to the other markets of the vendors[7]). For instance, IBM has assisted in several efforts to maintain a good code pedigree internally at IBM and externally for much smaller organizations[8]. Vendors could further sponsor more research to avoid damages. For example, more legal measures, which prevent intellectual property owners from hiding for too long (e.g. until some open contents have been widely adopted) before suing[9], could be further studied.

In short, open contents stakeholders are facing uncertainties surrounding intellectual property rights and care levels have been exercised to limit the scale of such problems ex ante. Given the complicated issues involved in these episodes, I will only

[5]See http://www.sco.com/scoip/lawsuits/, accessed Nov 1, 2009.

[6]MEMORANDUM DECISION AND ORDER, Civil Case No.2:04CV139DAK, IN THE UNITED STATES DISTRICT COURT FOR THE DISTRICT OF UTAH, CENTRAL DIVISION.

[7]For example, IBM researchers *P.G.Capek et al.* (2005) write, "We also saw in Linux the possibility of having a unified operating system on our platform...A strategy [at IBM] was planned that allowed us to add value for our customers in the areas, [which were] clearly in the broad area of what is called middleware, and not in operating systems." Also, IBM announced in 2001 to spend over $1 billion in the next three years on open source projects (*P.G.Capek et al.* (2005)).

[8]Such efforts include the Certificate of Originality for the code developed at IBM, the Developer's Certificate of Origin for the Linux kernel, and the Contributor License Agreement for the Apache Software Foundation. See Capek et al (2005), pp. 251, Open Source Development Lab (2005) and The Apache Software Foundation (2006).

[9] In view of *SCO v. IBM*, *Zittrain* (2004) argues that copyright law should be "construed in a way that does not permit a poisoned pea of unauthorized code under the mattress of a massive software project to effectively compromise the entire work". He discusses that copyright's statute of limitations might be applied to require those claiming copyright infringement to bring such claims within a three-year (or shorter) window stemming from the targeted software's initial public release of source code.

abstract in the next section slices of the episodes to capture certain decision problems in open content production I think are relevant to the research question presented earlier.

2.3 Theory

2.3.1 Setup

Consequences not fully specified in a contract can reduce investment (*Grossman and Hart* (1986) and *Hart and Moore* (1990)). Unspecified consequences can be thought of as unclear delineation of rights, which results from the absence of right to contract (*Cheung* (1970)) or the high transaction costs of specification. Without a detailed investigation of the transaction costs involved, it is inconclusive that any reduction in investment is socially inefficient. If it is due to high transaction costs, then one could argue that the status quo is efficient because society otherwise needs to find ways to reduce such transaction costs. If it is due to the absence of rights, then one could argue that the status quo is not efficient if the provision of rights is costless. This is because when property rights are clearly defined, social efficiency will be achieved by subsequent contracting as long as transaction costs are low (*Coase* (1960)). I will contrast the optimal choices when there is or is not a right to contract.

More specifically, I consider a case in which there are still high transaction costs to contract with Hidden, defined as an agent claiming to be the intellectual property right owner. Hidden, similar to what SCO has done, does not surface until later stages. However, I vary the transaction costs (or equivalently, for our purpose here, the rights) of contracting between innovators, value-adding vendors (resellers or redistributors) and users.

To model overlapping of rights in open contents, I present the decision problems of several active agents in the economy relevant to the open contents landscape: social planner, users, innovators, and vendors. In addition, Hidden is an inactive agent who passively collects receipts from users, innovators, and vendors.

In some bilateral-care accident or product liability models (*Landes and Posner* (1985), *Landes and Posner* (1987), *Miceli* (1997), and *Shavell* (1980)), each agent chooses care and activity levels to adjust damages (or monetary losses). They may or may not have engaged in a market transaction (e.g. a faulty purchased fan causes a house fire, versus an auto accident.) I use such models to incorporate a third party called vendors. Vendors may or may not engage in market exchanges with the innovators or the users but will choose some care and activity levels. The care levels here refer to the efforts, measured in monetary amount, made to avoid some expected damage paid to the inactive agent. The level of activity, Q, is the number of copies of the same information good distributed by the innovators and the vendors.

The damages are due to intellectual property infringements. They are paid to Hidden and thus one form[10] of unclear delineation of rights is incorporated in the model since it is not possible to enter into contractual arrangements with Hidden[11]. I, therefore, have not explicitly modeled the actions of this inactive agent. Now consider only the representative agent approach in modeling the active agents. Hereafter I use the singular and plural forms of these active agents interchangeably. Also, subscript $j = v, u, i$ stands for the vendor, user, and innovator. Let $K_j(Ql_j)$ be the total care cost of agent j when agent j chooses care level l_j for each of the Q copies of the information goods available in the market. Note that the care applies to all existing stocks of open contents. This captures the case in which all copies of the same information good is free from the liability of an infringing part if it is discovered once and is removed in the current and subsequent copies. Denote $D(l_v, l_i, l_u)$ the

[10]Another form arises when innovators, vendors and users cannot contract with each other. See discussions before Corollary II.3.

[11]Since Hidden is by construction hidden, there is no way to contract with them and thus its decision problem is absent in the model. This is not to say that there are no other intellectual property owners that you can contract with. For example, not all trolls are hidden if they jump out of the bush early and negotiate a contract with other agents.

unit expected damage for each of the Q copies of the information goods[12]. $D(\cdot)$ is a strictly concave function with $D_j < 0$.

The liability for active agent j, $\bar{s}_j$, is defined to be the fraction of D that j pays in expectation.

Let $b(Q)$ be the marginal consumption benefit for a representative user of the information good. There is diminishing marginal benefit because by assumption $b' < 0$[13]. Let $c_i(\cdot)$ be the total production cost of an innovator. R is the price paid to either the innovators or the vendors depending on who delivers the copy to the user.

Before I present the decision problems of the active agents, let us assume that the profit function of Hidden is:

$$\Pi_h = (1 - \theta)QD - F_h \tag{2.1}$$

where θ is the ratio of litigation costs due to intellectual property infringement lawsuits, and F_h is the fixed cost of having the court to rule that Hidden has a claim on the intellectual property with a positive probability. Such fixed cost captures, for example, that Hidden needs to incur a cost to produce part of the open contents[14].

2.3.2 The Users' Problem

The problem for the users is assumed to be equivalent to the one solved by a representative user. Assume that there is only one piece of information good to be produced, which requires a fixed cost of F_i. Innovators distribute q_i copies of it.

[12] The linearity of the total damages is only an approximation to actual damages in the copyright context.

[13] One could argue that for open contents such as open source software, there are network effects because the more copies circulated the higher is the marginal value to the users because they could share files with each other. However, some form of diminishing returns must be showing at some point to rule out infinite sales, which we do not observe in the real world. For simplicity, I have considered only cases in which diminishing marginal benefit is consistent with the cases that either Q is already expected to be so large that there is no more positive network effects, or there are no intrinsic network effects.

[14] One could further extend this model by allowing Hidden to choose some actions such as the timing of litigation.

Vendors distribute q_v of it. The user buys from either of them. In equilibrium,

$$q_v + q_i = Q \tag{2.2}$$

The risk-neutral user buys a total of Q copies at a unit price of R each, and chooses a care level l_u to maximize:

$$U = \int_0^Q b(h)dh - Q[R + \bar{s}_u D(l_v, l_i, l_u)] - K_u(Ql_u) \tag{2.3}$$

where $\frac{\partial R}{\partial Q} = 0$[15], and $\bar{s}_u$ is the expected liability share of the users for the damage. The care level refers to the caution the user takes to ensure that the intellectual property rights are cleared, and that the information good is properly chosen, maintained and operated. The first order conditions are[16]:

$$-\frac{\partial R}{\partial l_u} = \bar{s}_u D_{l_u} + K'_u \tag{2.4}$$

$$b(Q) = R + \bar{s}_u D + K'_u l_u \tag{2.5}$$

2.3.3 The Innovator's Problem

In this model, an information good is not serviceable unless it is thoroughly documented and provided with customer support. For instance, a large q_i increases the need to provide differentiated documentation for different types of users. For each copy sold by the innovator, a marginal cost of $c'_i(\cdot)$ will be incurred by the innovator. The total variable cost of production is $c_i(\cdot)$. In addition, the innovator also chooses a care level l_i for each Q (important, not q_i, because it is open content), to directly adjust the total expected damage QD. The total care cost, $K_i(Ql_i)$, increases with

[15]Recall that this user is a representative user, who represents n identical users who are small relative to the whole market. That is why they are price-takers.

[16]The Leibnitz formula is used to derive the result $\frac{d}{dQ}\int_0^Q b(h)dh = b(Q)$.

Q. This is to capture the case that the innovator needs to patch each of the copies circulated to remove the infringing code.

For simplicity, there is only one innovator who is selected from competition. Thus, the innovator makes zero profit. The problem for the innovator is to choose q_i and l_i to maximize:

$$\Pi_i \equiv q_i R - F_i - c_i(q_i) - Q\bar{s}_i D(l_v, l_i, l_u) - K_i(Ql_i) \tag{2.6}$$

where $\bar{s}_i$ is the expected liability share of the innovator. The first order conditions are:

$$q_i \frac{\partial R}{\partial l_i} = Q\bar{s}_i D_{l_i} + QK_i' \tag{2.7}$$
$$R = c_i'(q_i) + \bar{s}_i D + K_i' l_i \tag{2.8}$$

2.3.4 The Vendor's Problem

There is one vendor who is selected from competition. Thus, the vendor makes zero profit. The vendor competes with the innovator to resell the open contents since downstream licensing is royalty free. The vendor incurs a cost $c_v(\cdot)$ to redistribute some copies of the good created by the innovator.

On the other hand, this vendor enjoys some net spillover benefits, $\omega(Q)$, of the stock of copies in the economy. For example, the vendor might be selling a complementary product in another market. The vendor's profit function is:

$$\Pi_v \equiv q_v R - c_v(q_v) + \omega(Q) - Q\bar{s}_v D(l_v, l_i, l_u) - K_v(Ql_v) \tag{2.9}$$

It implies that even if $q_v = 0$, as long as $q_i > 0$, this vendor might find it beneficial to incur $K_v(Ql_v)$ to adjust the total expected damage QD[17]. The first order conditions

[17] The debate (*Boldrin and Levine* (2002), *Klein et al.* (2002), and *Romer* (2002)) focuses on the necessity of intellectual property in face of the new sharing technologies such as Napster. This paper fills a gap in the debate by enlarging the scope of analysis to include information goods such as

are:

$$q_v \frac{\partial R}{\partial l_v} = Q\bar{s}_v D_{l_v} + QK'_v \quad (2.10)$$

$$R + \omega'(Q) = c'_v(q_v) + \bar{s}_v D + K'_v l_v \quad (2.11)$$

2.3.5 The Decentralized Equilibrium

(2.2), (2.4), (2.7) and (2.10) together with the five equations below characterize the equilibrium given the liability rules. Since $\bar{s}_v + \bar{s}_u + \bar{s}_i = 1$, the decentralized equilibrium level q_i^+ satisfies the following equation, obtained from the combination of (2.5) and (2.8)[18]:

$$b(Q) = c'_i(q_i) + (\bar{s}_u + \bar{s}_i)D + K'_i l_i + K'_u l_u \quad (2.12)$$

Also, the decentralized equilibrium level q_v^+ satisfies the following equation, obtained from the combination of (2.5) and (2.11)[19]:

$$b(Q) = -\omega'(Q) + c'_v(q_v) + (\bar{s}_u + \bar{s}_v)D + K'_v l_v + K'_u l_u \quad (2.13)$$

Free entry implies these zero profit conditions of the innovator, vendor and Hidden, respectively:

$$q_i R = F_i + c_i(q_i) + Q\bar{s}_i D + K_i(Ql_i) \quad (2.14)$$

$$q_v R + \omega(Q) = c_v(q_v) + Q\bar{s}_v D + K_v(Ql_v) \quad (2.15)$$

$$(1-\theta)QD = F_h \quad (2.16)$$

---

software files. The sharing of software allows resellers to help increase the quality of the software by, for example, sharing the efforts to fix software vulnerabilities.

[18] To be more precise, q_i^+ is still a best response function wrt q_v. But we do not need to explicitly solve for it for comparative statics.

[19] Similarly, q_v^+ is still a best response function wrt q_i.

2.3.6 The Centralized Equilibrium

The social planner's problem I use here is to choose l_v, l_u, l_i, q_i and q_v to maximize the total welfare in this additive form:

$$
\begin{aligned}
W &= U + \Pi_i + \Pi_v + \Pi_h && (2.17)\\
&= \int_0^Q b(h)dh + \omega(Q) - c_i(q_i) - c_v(q_v) - K_v(Ql_v) \\
&\quad -K_u(Ql_u) - K_i(Ql_i) - QD + (1-\theta)QD - F_i - F_h && (2.18)\\
&= \int_0^Q b(h)dh + \omega(Q) - c_i(q_i) - c_v(q_v) - K_v(Ql_v) && (2.19)\\
&\quad -K_u(Ql_u) - K_i(Ql_i) - \theta QD - F_i - F_h && (2.20)
\end{aligned}
$$

Conditional on there being a litigation, $(1-\theta)QD$ is just a transfer between the agents, if the social planner does not care about its distribution among the agents, the role of liability shares is just to induce the most efficient care takers to reduce the damages. That is why only θ portion of the total expected damage is left in the last equation because the social planner still cares about how to reduce the dissipative litigation costs. Considering interior solutions[20], the first order conditions are:

$$
\begin{aligned}
K_v' + \theta D_{l_v} &= 0 && (2.21)\\
K_u' + \theta D_{l_u} &= 0 && (2.22)\\
K_i' + \theta D_{l_i} &= 0 && (2.23)\\
b(Q) &= -\omega'(Q) + c_i'(q_i) + K_v' l_v + K_u' l_u + K_i' l_i + \theta D && (2.24)\\
b(Q) &= -\omega'(Q) + c_v'(q_v) + K_v' l_v + K_u' l_u + K_i' l_i + \theta D && (2.25)
\end{aligned}
$$

[20] Here I assume the Inada conditions $\lim_{l_j \to 0} \frac{\partial D(\cdot)}{\partial l_j} = -\infty$ and $\lim_{l_j \to \infty} \frac{\partial D(\cdot)}{\partial l_j} = 0$. These guarantee a unique interior solution for the care levels. For q_v and q_i, we assume that it is strictly positive because we have to start with some strictly positive q_i for vendors to redistribute. $q_v = 0$ is an uninteresting case.

The last two equations together imply:

$$c_v'(q_v) = c_i'(q_i) \tag{2.26}$$

2.3.7 Efficiency of Decentralization

When the values of the decentralized and centralized equilibrium variables (denoted by + and $*$) coincide, the decentralized choices are efficient.

Quantities

Proposition II.1. Given some strictly positive care levels, the liability rules are irrelevant for q_i^* and q_v^*. But the efficient quantities levels of q_i^* and q_v^* are not necessarily obtained from the decentralized equilibrium. In fact, $q_i^* = q_i^+$ and $q_v^* = q_v^+$ only if $K_i'l_i + \bar{s}_i D = K_v'l_v + \bar{s}_v D - \omega'(Q)$.

Proof. $\bar{s}_v, \bar{s}_u$, and $\bar{s}_i$ are absent in (2.24) and (2.25). Recall that the centralized equilibrium requires that $c_v'(q_v^*) = c_i'(q_i^*)$. For this to hold at the decentralized level, from (2.12) and (2.13), we have $c_v'(q_v^+) = c_i'(q_i^+) \iff K_i'l_i + \bar{s}_i D = K_v'l_v + \bar{s}_v D - \omega'(Q)$ □

The intuition is the following. The marginal revenue of redistribution is constant. For both the innovator and vendor to make zero profit, their total marginal costs should be the same. From (2.26), the social planner wants the marginal distribution costs to be the same for both the innovator and vendor. This implies that the rest of the marginal costs must be the same. The rest of the marginal costs for the innovator are $K_i'l_i + \bar{s}_i D$ and the rest for the vendor are $K_v'l_v + \bar{s}_v D - \omega'(Q)$[21].

[21] One can also see it this way. The zero profit condition of the innovator implies that $R = c_i'(q_i) + \bar{s}_i D + K_i'l_i$ and the zero profit condition of the vendor implies that $R = c_v'(q_v) + \bar{s}_v D + K_v'l_v - \omega'(Q)$. Equating these two implications and then apply $c_v'(q_v^+) = c_i'(q_i^+)$, we have $K_i'l_i + \bar{s}_i D = K_v'l_v + \bar{s}_v D - \omega'(Q)$.

Rewriting the condition $K_i' l_i + \bar{s}_i D = K_v' l_v + \bar{s}_v D - \omega'(Q)$, we have $(\bar{s}_v - \bar{s}_i)D = K_i' l_i - K_v' l_v + \omega'(Q)$. One implication is that to have efficient quantities produced, a necessary condition is that the vendor should bear more liability than the innovator when the marginal spillover effect $\omega'(Q)$ and the innovator's care costs of the marginal copy, $K_i' l_i$, are high relative to the vendor's care costs of the marginal copy, $K_v' l_v$.

Care Levels Now, let us compare the care levels by comparing the equilibrium care levels l_v^+, l_u^+, and l_i^+ that satisfy (2.10), (2.4), and (2.7) with l_v^*, l_u^* and l_i^* that satisfy (2.21), (2.22), and (2.23).

Proposition II.2. Efficient care levels can be achieved when these necessary conditions are satisfied:

$$\bar{s}_i = \theta + \frac{q_i \frac{\partial R}{\partial l_i}}{QD_{l_i}} \tag{2.27}$$

$$\bar{s}_v = \theta + \frac{q_v \frac{\partial R}{\partial l_v}}{QD_{l_v}} \tag{2.28}$$

$$\bar{s}_u = \theta - \frac{\frac{\partial R}{\partial l_u}}{D_{l_u}} \tag{2.29}$$

Proof. Equating (2.7) with (2.23), we have: $\bar{s}_i = \theta + \frac{q_i \frac{\partial R}{\partial l_i}}{QD_{l_i}}$. Equating (2.10) with (2.21), we have: $\bar{s}_v = \theta + \frac{q_v \frac{\partial R}{\partial l_v}}{QD_{l_v}}$. Equating (2.4) with (2.22), we have: $\bar{s}_u = \theta - \frac{\frac{\partial R}{\partial l_u}}{QD_{l_u}}$. □

Note that for $j = i, v, \bar{s}_j$ is increasing in the litigation cost, j's share of quantity supplied (q_j/Q), and the rate of change of the unit price w.r.t. j's care level. $\bar{s}_j$ is decreasing in the rate of change of the damage function w.r.t. j's care level. The intuition is that j should bear a higher liability share cost if it is supplying relatively more than the other supplier else there will not be zero profits because j has to exercise care to the copies distributed by itself and the other supplier. j should bear an even higher liability share cost if it is compensated more through the unit revenue for more of its care level else its zero condition will be violated. But j should bear a lower liability share cost if D_{l_i} increases, that is, it is becoming less effective in reducing damage through its care. $\bar{s}_u$ can be interpreted in a similar way but with the direction reversed for the rate of changes.

Recall that in the beginning of this theory section, I want to model some cases when there are high transaction costs or some rights are absent. Now consider the cases if some forms of bargaining are not feasible because of these reasons. Specifically, consider these restrictions:

$$\bar{s}_v, \bar{s}_u, \bar{s}_i \in [0, 1] \tag{2.30}$$

and

$$\text{For some } j, \frac{\partial R}{\partial l_j} = 0. \tag{2.31}$$

The lower bound of the first restriction says that one cannot take the liability as a revenue source. Its upper bound implies that one cannot pay more than what the damage is worth. The second restriction says that the price could be independent of either l_v, l_u or l_i.

Here are several corollaries that hold largely because some zero profit condition(s) must be violated otherwise:

Corollary II.3.

$$\forall j = i, v : \frac{\partial R}{\partial l_j} = 0 \iff \bar{s}_j = \theta \tag{2.32}$$

$$\forall j, j' = i, v : \frac{\partial R}{\partial l_j} = 0 \iff \bar{s}_{j'} = 0, j \neq j' \tag{2.33}$$

Proof. The first equation is trivial by Proposition II.2 since $q_i, q_v, D_{l_v} \neq 0$. For the second equation, from the zero profit condition of the vendor (2.15), $\frac{\partial R}{\partial l_i} = 0 \iff \bar{s}_v = 0$. Similarly, from the zero profit condition of the innovator (2.14), $\frac{\partial R}{\partial l_v} = 0 \iff \bar{s}_i = 0$. □

For $Q > 0$, $\frac{\partial R}{\partial l_j} = 0$ implies that the first order condition of innovator or vendor becomes $\bar{s}_j D_{l_j} = K_j'$. This is a marginal revenue equals marginal cost condition for the individual's optimization problem. Recall that the corresponding marginal revenue equals marginal cost condition for the social planner's optimization problem is: $\theta D_{l_j} = K_j'$. So for the decentralized choices of care levels to be socially optimal, these two conditions need to be equal, giving $\bar{s}_j = \theta$.

Corollary II.4. *When the price is invariant to the care levels of the innovator and the vendor, that is,* $\frac{\partial R}{\partial l_i} = \frac{\partial R}{\partial l_v} = 0$, *efficient care levels cannot be achieved if* $\theta \neq 0$.

Proof. By the previous corollary, when $\frac{\partial R}{\partial l_i} = \frac{\partial R}{\partial l_v} = 0, \bar{s}_v = \bar{s}_i = 0$. This violates $\bar{s}_v = \bar{s}_i = \theta$ by the previous corollary since $\theta \neq 0$. □

Corollary II.5. *If* $\theta \geq \frac{1}{2}, \bar{s}_v > 0$ *and* $\bar{s}_i > 0$, *the decentralized choices are efficient only if* $\bar{s}_u < 0$.

Proof. When $\bar{s}_v > 0$, the zero profit condition of the vendor (2.15) implies that $\frac{\partial R}{\partial l_i} < 0$. Then by Proposition (II.2), $\bar{s}_i > \theta$. Similarly, $\bar{s}_i > 0$ and the zero profit condition of the innovator (2.14) implies that $\frac{\partial R}{\partial lv} < 0$ and $\bar{s}_v > \theta$ by Proposition (II.2). Together with $\bar{s}_v + \bar{s}_u + \bar{s}_i = 1$, we have $\bar{s}_u < 1 - 2\theta \leq 0$ if $\theta \geq \frac{1}{2}$. □

One implication is that in the no liability to users case ($\bar{s}_u = 0$), efficient care levels cannot be obtained if the litigation costs are too high ($\theta \geq \frac{1}{2}$).

Corollary II.6. *If* $\bar{s}_v = \bar{s}_i = 0$, *efficient care levels cannot be achieved if* $\theta \neq 0$.

Proof. $\bar{s}_v = \bar{s}_i = 0 \implies \frac{\partial R}{\partial l_i} = \frac{\partial R}{\partial l_v} = 0$ by Corollary (II.3). Then by Corollary (II.4), efficient care levels cannot be achieved if $\theta \neq 0$. □

Another implication is that for the no liability to the innovators and vendors case ($\bar{s}_v = \bar{s}_i = 0$), commonly used in open content licenses, efficient care levels cannot be achieved if there are non-zero litigation costs ($\theta \neq 0$).

2.4 Conclusions

I used a tort model to study the inclusion of value-adding resellers (vendors) who do not need to pay the original sellers (innovators) for production. I modeled after the SCO-Linux controversy to include an agent who receives a positive expected payment in intellectual property lawsuits but it is hard for other agents to contract with this agent ex ante. I then analyzed how the litigation between this agent, vendors, innovators and users affects care levels and quantities distributed.

Some main results here confirm with the standard results that in general efficiency requires the lowest cost agents to engage in activity until their marginal costs equal to that of other agents. The main contributions here are the derivations of some necessary conditions for efficiency and sufficient conditions for inefficiency in the context of open contents.

For efficient quantities, it is necessary for the vendors to bear more liability than the innovator when the marginal spillover effect and the innovator's care costs of the marginal copy are high relative to the vendor's care costs of the marginal copy. For efficient care, it is necessary for care levels to obey the implicit analytical forms of the optimal liability shares I have derived.

For inefficient care, I have derived some sufficient conditions related to the interaction of liability shares and litigation costs. For example, in the no liability to users case, efficient care levels cannot be obtained if the litigation costs are too high. In the no liability to the innovators and vendors case commonly used in open content licenses, efficient care levels cannot be achieved if there are non-zero litigation costs.

This research is not without limitations. One cannot immediately conclude that the real world values are not optimal when there is a deviation from the theoretical values because the transaction costs associated with one or more variables could simply be too high. Further empirical research could be done to identify what measures, with less transaction costs, are used for adjustment in place of those variables that appear to be deviating from the theoretical values. For example, the theoretical liability shares here could be proxied by several non-mutually exclusive observables in addition to those provisions in the open content licenses. If the liability shares in open content licenses are too rigid, liability adjusting measures might emerge to clear the market.

CHAPTER III

Modularity and Team Size in Open Content Experiments

3.1 Introduction

The open source movement has already challenged the biggest players in the computer industry. Attempts have been made to broaden the scope to areas other than software. This paper focuses on one of these areas called open contents. Contents, such as software, music, films or books, are defined here to be open if one is free to use, reuse, and redistribute them[1]. How to ensure success in such area using the open source concept? Should principles prevalent in coding be also applied to contents? One principle I mainly investigate here is modularity with different team sizes.

Modularity is deeply rooted in the computer science literature[2]. The concept of information hiding, pioneered by *Parnas* (1972), says that non-modularity is not optimal if the inner workings of a module overlap with the responsibility of another module. For instance, non-modularity implies that errors are serially correlated across

[1] This is from the Open Knowledge Definition website, which claims this to be the simplest version of their more complete definition available at: http://www.opendefinition.org/, accessed December 15, 2009. Other definitions exist, for example, see *Newmarch* (2000) and *Liang* (2004). There are a few related concepts such as user-generated contents (*Krumm et al.* (2008)), open innovation (*Chesbrough* (2004)), user innovation (*Von Hippel and Von Krogh* (2003)) and the like. A comparison between these concepts is outside the scope of this research.

[2] *Simon* (1962) and *Alexander* (1964) are some of the earliest works.

modules. Various experimental studies (e.g. see *Camerer* (2003) pp. 383 for a review) show that it is easier to achieve a socially inefficient outcomes (even though more socially efficient outcomes are also Nash) as team size increases when non-modularity takes the form of minimum effort games[3,4]. All these are consistent with the following theories in the open source context. *Baldwin and Clark* (2006) (pp. 1126) show theoretically that social efficiency decreases because non-modularity leads to a higher free-riding level among open source developers. Varying team size and modularity, *Johnson* (2002) (pp. 658) shows theoretically that non-modularity is socially inefficient (due to free-riding) only for large teams of developers.

However, both *Baldwin and Clark* (2006) and *Johnson* (2002) assume that the costs of development are independent across individuals, implying that the spillover of know-how does not matter in cost saving. This assumption is perhaps a key deviation from the essential features of open contents. In practice, individuals share with each other code or methods used. This paper relaxes this assumption by allowing some spillover of know-hows. Meanwhile, the game settings here are also quite different[5]. This is because this paper does not aim to directly test the above theories in an exact environment. I only report the results on similar considerations from a laboratory setting that perhaps captures more external validity than those theoretical studies, and that allows us to vary team size and the degree of modularity in a tractable manner.

Section 3.2 presents the experimental design and procedures. Hypotheses are presented in Section 3.3. An empirical analysis is presented in Section 3.4. Section

[3]A minimum game takes this form. Individual i chooses an effort level from the set of non-negative integers to maximize his payoff determined by the minimum of the effort levels of all team members: $\text{Payoff}_i = \min_{i=1 \text{ to } N}\{\text{effort}_i\} - \text{cost}_i \times \text{effort}_i$. There are multiple equilibria in this game. *Anderson et al.* (2001) offers a review of the experimental results and plausible theories.

[4]This is a particularly important class of games (*Camerer* (2003), pp. 376-7).

[5]For example, the above theoretical works only study simultaneous games with restricted cost structures while this experiment allows for sequential games without such restrictions. One tradeoff is that the game is too complicated to solve. That said, I will not provide a Nash nor claim that such equilibrium exists.

3.5 concludes. Appendix A reviews the strategies for the game the subjects were asked to solve. Appendix B contains the instructions to subjects.

3.2 Experiment

The experiment is a factorial design with modularity and team size as factors. An open content production process is simulated based on a popular board game called MASTERMIND[6]. The next subsection explains the rules of MASTERMIND and provides justifications about using it for open content experiments. Appendix A reviews the strategies that solve the traditional (standalone) MASTERMIND. The second subsection presents the experimental design

3.2.1 Open Contents and MASTERMIND

The rules of MASTERMIND are simple. In a popular version of MASTERMIND, there are pegs in 6 colors used by a combination–breaker and pegs in black and white used by the combination–setter. For each game, a combination of 4 color pegs is set secretly by the combination–setter so the search space is 6^4. The combination–breaker's task is to guess the secret combination. For each guess, the combination–setter uses black and/or white pegs to give hints to the combination–breaker. A black peg means that the color and position of a guessed peg are correct; a white peg means that the color of a guessed peg is correct but not the position.

Mathematically, the secret combination is defined as $S = \{s_1, s_2, ..., s_N\}$, where s_n is the n^{th} peg with color s, $s \in [1, k]$, k = the number of colors, and N = the length of the combination or the number of slots.

The t^{th} guess is defined as $h^t = \{h_1^t, h_2^t, ..., h_N^t\}$, where h_n^t is the n^{th} peg with color

[6]MASTERMIND is a registered trademark of Hasbro International Inc. It is not uncommon to adopt ready-made games in experiments. For instance, *Andreoni and Varian* (1999) ran an experiment using a card game a few years ago.

h, $h \in [1, k]$. $H = \{h^1, ..., h^t\}$ is a history of guesses[7].

H in MASTERMIND is a reasonable proxy for open contents in a sense that both H and many examples of open contents contain an algorithm[8] that is publicly observable, and H is free to use, reuse, and distribute in the experiment.

3.2.2 Experimental Design

This experiment retained the rules of MASTERMIND except that at any time subjects could post unfinished games to the public pool where everyone could see the complete history of moves of the posted games. Each game posted must be accompanied by a possibly different non-negative commission price, chosen by the poster. The one who solved it first got the commission price transferred from the reward of the poster to this person. Anyone who solved a posted game must clone the posted game first so a copy of the history of work already done would be displayed on the screen for this person to continue the work. The exact number of clones cannot be observed by the participants. Everyone was allotted three games, each with a random secret combination, in each period. There was a $1 potential reward for either solving a game by oneself or having other people to solve it through the public pool.

The experiment is a two-by-two factorial design with production i and team size j as factors where i =modularity (M) or non-modularity (NM) and j =large (L) or small (S). In the modular production, the potential reward was immediately credited to the subjects' earnings. In the non-modular production, the potential reward was credited only if all allotted games for every subject were solved–this is also called the

[7]Each hint is the pair of numbers $b(h^t, S)$ and $w(h^t, S)$, that is, the number of black and white pegs. $b(h^t, S)$ is the number of subscripts n such that $s_n = h_n$. $w(h^t, S) = [\max_p b(h^t, p)] - b(h^t, S)$, where p is a vector from the set of vectors containing all permutations of the S vector. See *Chvatal* (1983).

[8]By categorizing the works of Alan Turing, Kurt Godel, and Alonzo Church (1930's) on Turing Machines and Recursive Functional Theory, *Dennett* (1995) listed these features of an algorithm: 1. Substrate neutral, only logic matters. 2. Straightforward recipe. 3. Deliver wanted results every time.

O-ring requirement[9]. In other words, the total production (or payoff) of a team was zero if either one of its members failed in the NM production.

In each session, there were 10 periods, each of which was seven minutes long. Each period ended when the time limit was reached.

3.2.3 Experimental Procedures

The experiment was conducted on networked computers with human subjects in the School of Information Lab at the University of Michigan. The author developed a software that is a collaborative version of MASTERMIND. There were 16 subjects for the large teams and 4 subjects for the small teams. A total of 88 students were recruited[10]. They were mostly undergraduate students at the University of Michigan. Students already subscribed to the mailing lists of the labs received notice of the experiment. The interested students then signed up for the experiment through an online recruitment system on a first-come-first-served basis. Each session lasted for two hours. No subjects participated in more than one session. Almost all students finished the instructions in half an hour. A quiz was administered before the experiment began. The experimenter went to the carrels to check the answers. If there was a mistake, the experimenter explained to him or her individually. Individual anonymity was maintained through out the experiment; subjects did not know the real world identities of the players in the software. There was a two-minute trial period before Period 1. The average payoff without the show-up fee was \$15.5[11]. The

[9] It is so named, also by *Kremer* (1993), to capture the idea that a very insignificant part of a system can cause a complete failure. This is exemplified by the explosion of the space shuttle *Challenger* in 1986, which was caused by the failure of the O–rings.

[10] The size of the large team was chosen to accommodate the capacity of the lab, and the size of the small teams was chosen to allow greater separation of two sizes in case less than 16 subjects showed up. A size of less than 4 seemed to be too small and anonymity could become a big issue.

[11] Due to the nature of the non-modular production, students could end up getting nothing but the show-up fee. The show-up fee was adjusted upwards for all subjects in the same session after the experiment if there were subjects getting particularly low payments; this had not be announced during the experiment. The adjustments were made such that the total payoff was around \$20.

Team Size	Production	Number of Subjects Per Session	Number of Sessions
Large	NM	16	2
Large	M	16	2
Small	NM	4	3
Small	M	4	3

Figure 3.1: Features of Experimental Design

features of the whole experiment is summarized in Figure 3.1[12].

3.3 Hypotheses

The general null hypothesis is no difference. The following hypotheses are the alternative hypotheses.

In both *Baldwin and Clark* (2006) and *Johnson* (2002), an individual free-rides if he or she does not complete a task while some other individuals do. In our experiment, this is analogous to this: A subject free-rides if he or she sets a commission price of zero in a posted game. The following hypothesis is formulated according to the above analogy[13]:

Hypothesis III.1. Free-riding in the modular production is less than that in the non-modular production.

Issac and Walker (1988) and *Issac et al.* (1994) find that group size does not

[12]We also conducted some with-subject pilot sessions, which together with the 2-by-2 design here would complete a Solomon four-group design. Statistical tests for Solomon four-group design are known to be tough. Not until the recent decade do we find perhaps more successful methods such as *van Engelenburg* (1999): "Although the [Solomon four-group] design has been proposed half a century ago, no proper data analysis techniques have been available. In this paper, it is described how data from the Solomon four-group design can be properly analyzed using maximum likelihood regression analysis." Unfortunately, I cannot rely on this method because it turned out that the data violate the normality assumption required by the maximum likelihood regression. One could also perform other statistical tests but none of these are directly related to the hypotheses here or do they fully utilize all the available data in the design.

[13]I will show in the results section that the statistical results are quite robust to different measures of free-riding.

matter when the cost of contribution is low but group size increases contribution at a decreasing rate when the cost of contribution is high. *Andreoni* (2007) shows that as group size increases, the average contribution will decline. This is not because of increased free-riding but congested altruism changes the value of the social surplus to the contributor[14]. However, (*Kagel et al.* (1995), pp. 151-3) claim that most economists expect group size to be positively related to free-riding. It seems important to test the effects of group size against such "common sense" of economists:

Hypothesis III.2. Free-riding is less for small teams than that in large teams.

In *Johnson* (2002), when the number of developers exceeds a threshold, modular software is more likely to be completed. Else, non-modular software is more likely to be completed. This is because "nonmodularity will sometimes temper [with] free-riding" (*Johnson* (2002), pp. 660). The next two hypotheses are consistent with this.

Hypothesis III.3. Free-riding is less (more) in non-modular than modular production for small (large) teams.

Hypothesis III.4. Efficiency is higher (lower) in non-modular than modular production for small (large) teams.

Consistent with *Parnas* (1972), the following seems to be consistent with the computer scientists' expectations:

[14] *Andreoni* (2007) models contribution to groups as a congestible public good. The congestion is in the hearts of the altruists rather than in the technology of the public good. Assume that Π_0 is the total social surplus generated for others by the dollars forfeited. Let $\pi_0 = \Pi_0/n$ be the average surplus for others. For a non-congested good, an individual contributor views the contribution, g, as being the total social surplus, independent of n. Then $g_0 = \Pi_0 = n\pi_0$. For a congested good, an individual contributor views the contribution, g, as being the average social surplus, independent of n. Then $g_1 = \Pi_0/n = \pi_0$. Assuming that the actual behavior might be a mixture of both, captured by $g = g_0^b g_1^{1-b} = n^b \pi_0$, he estimates that b is 0.68. That is, as group size increases, altruism of the givers is congested and the value of the contribution to the giver does not grow proportionately with the social value of the public good.

Hypothesis III.5. Efficiency is higher in the modular production than in the non-modular production.

If one believes that this experiment captures some salient features of the minimum effort games, the following hypothesis seems reasonable because it is hard to coordinate with more team members to reach the more efficient equilibrium in such games (see *Camerer* (2003), pp. 383).

Hypothesis III.6. In the non-modular production, efficiency is higher for small teams.

In contrast to *Baldwin and Clark* (2006) and *Johnson* (2002), this paper allows some spillover of know-hows. A question is whether subjects would behave such that the usual behavior in the minimum effort games no longer hold. That is, some people choose a rather high effort level in the current period such that their knowledge can be learned by others to solve games in future periods. Consistent with this suspicion, the next hypothesis is formulated as:

Hypothesis III.7. Spillover is higher in the non-modular production.

3.4 Results

There are three dependent variables: free-riding, efficiency and spillover.

Free-riding is measured using three methods. Throughout the analysis, I stick with the first method and list the discrepancies whenever it applies. The first method measures the percentage of posted games set at zero commission with respect to all allotted games. The second method uses the percentage of posted games set at zero commission with respect to all posted games. The third method measures free-riding the same as the first method except that I only count those posted games, set a zero commission, that have been solved by a person other than the poster. The last method is used to capture the supply of and the demand for free-riding.

Efficiency is measured as the percentage of profits made over maximum profits. I also use a second measure, the percentage of completed games over all allotted games. These two measures coincide in the modular production but differ in the non-modular production. If only one game were not solved in the non-modular production, the first measure gives zero efficiency but the second gives positive efficiency.

Spillover is measured as the percentage of posted games over total allotted games. One can argue that for knowledge to be spread, it is necessary that a game must be posted first. In this sense, unless a game spreads negative know-hows, spillover should be positively related to the number of posted games.

In Figure 3.2, I group all data into four cells varying modularity and team size. The plots only use the first measures; the statistical analyses will test other measures as well.

Here are some casual visual inspection results. It seems somewhat true that free-riding is less for small teams than for large teams, especially for latter periods and for large teams. Small teams seem free-ride more in the non-modular production than in the modular production. Efficiency seems higher in the modular production. In the non-modular production, small teams seem more efficient especially for latter periods. It seems that spillover is significantly higher for large teams.

In the statistical analyses, I first used an ANOVA. Standard ANOVA assumes independence, normality, and homoskedasticity of errors terms. The data do not satisfy the last two. I still performed ANOVA on these data because *Conover and Iman* (1980) suggest that ANOVA can still be performed the usual way after rank transforming the dependent variables.

The k^{th} observation in cell (i, j) is specified as follows:

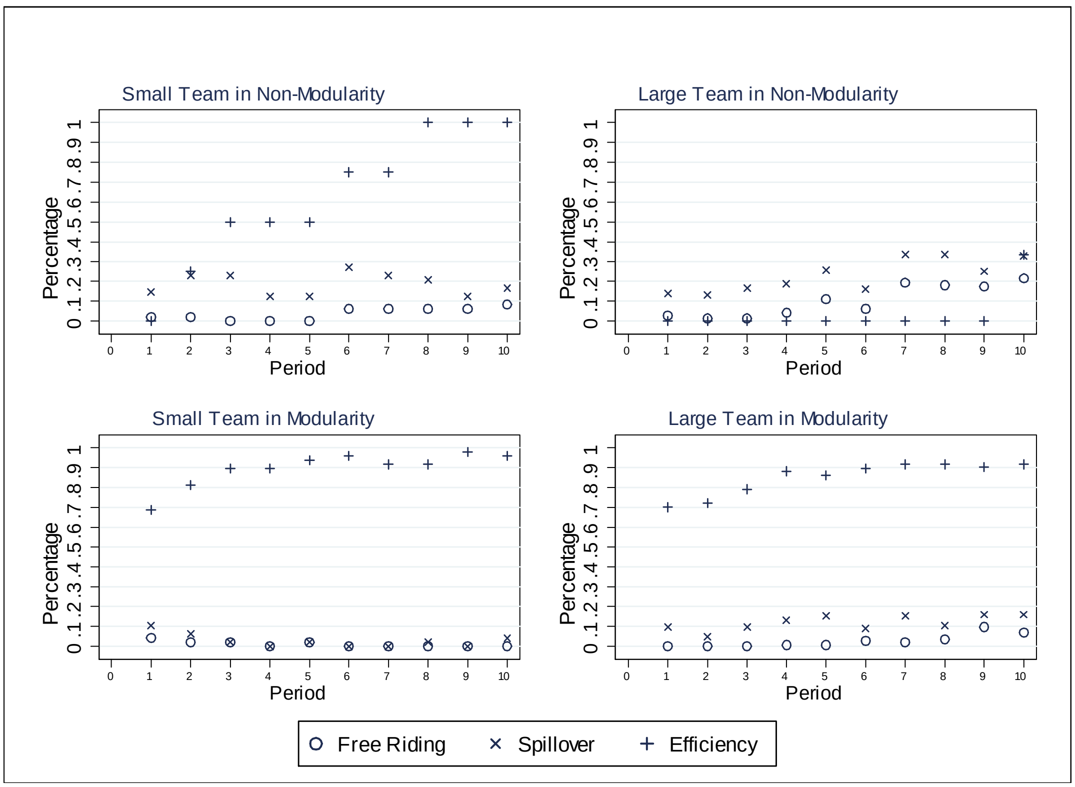


Figure 3.2: Percentages of Free-riding, Spillover, and Efficiency Varying Modularity and Team Size

$$\text{Dependent Variable}_{ijk} = \mu + \text{Team Size}_i + \text{Modularity}_j + \text{Team Size}_i \times \text{Modularity}_j + \epsilon_{ijk} \qquad (3.1)$$

Here are the main results using the Tukey-Kramer test for pairwise comparisons at the 5% significance level (please refer to Figure 3.3 for test statistics and critical values):

Result III.8. There is significantly less free-riding for small teams than that in large teams.

Result III.9. In the non-modular production, small teams are significantly more efficient[15].

Result III.10. There is significantly more spillover in the non-modular production.

Result III.11. There is significantly less free-riding in the modular production than that in the non-modular production only for large teams.

Result III.12. Efficiency in the modular production is significantly higher than that in the non-modular production for large and small teams[16].

Result III.13. There is significantly more spillover for large teams.

The overall results are the following. Hypotheses III.1, III.3, III.4 are partly rejected, and hypotheses III.2, III.5, III.6 and III.7 cannot be rejected. The test cannot reject a result not mentioned in all hypotheses: there was a higher percentage of spillover for large teams. To summarize, large teams were associated with a higher free-riding level than small teams. Free-riding was more severe when large teams

[15] This is only true for the first measure of efficiency.
[16] This is only true for the first measure of efficiency.

Variable	Measure	Held Constant[1]	Means Comparison Between	Means Difference	Test Statistics
Free-riding	First	S	NM & M	0.00	0.00
		L	NM & M	42.45	6.05*
		NM	S & L	-91.05	14.28*
		M	S & L	-48.80	7.65*
	Second	S	NM & M	0.00	0.00
		L	NM & M	34.60	4.74*
		NM	S & L	-88.50	13.30*
		M	S & L	-53.90	8.10*
	Third	S	NM & M	0.00	0.00
		L	NM & M	60.30	8.87*
		NM	S & L	-85.55	13.79*
		M	S & L	-25.25	4.07*
Efficiency	First	S	NM & M	-21.33	4.07*
		L	NM & M	-70.20	10.93*
		NM	S & L	61.43	10.47*
		M	S & L	12.57	2.14
	Second	S	NM & M	5.10	0.90
		L	NM & M	21.95	3.16*
		NM	S & L	10.03	1.58
		M	S & L	26.88	4.24*
Spillover	First	S	NM & M	64.63	11.24*
		L	NM & M	38.55	5.47*
		NM	S & L	-32.82	5.11*
		M	S & L	-58.90	9.16*

Note:
1. S, L, NM, and M stand for small teams, large teams, non-modularity, and modularity.
2. The critical value at the 5% significance level for a one-tailed test is 2.35. An asterisk indicates that the corresponding difference in means is significant at this level.
3. The means difference is obtained from the substraction of the first group mean by the second group mean in the "Means Comparison Between" column.

Figure 3.3: Tukey-Kramer Tests of Difference in Means

work in the non-modular production. There was a higher percentage of spillover in the non-modular production, especially for large teams. When efficiency is measured as the percentage of profits made over maximum profits, small teams were more efficient than large teams in the non-modular production and efficiency was higher in the modular production irrespective of team size.

3.5 Conclusions

This paper reports experimental results on open contents, which are free to use, reuse, and distribute.

Price (both pecuniary and non-pecuniary) often drives the allocation of resources. However, it is sometimes difficult to measure the difficulty of a task, even less so by a central authority. If price were used as a measure, it can only be a rather imperfect signal. This experiment documents a case in which price was at times not used to coordinate resources in open contents where production was decentralized. Free-riding, measured as zero price to helpers, was prevalent in the experiment. Large teams were associated with a higher free-riding level than small teams, and free-riding was more severe when large teams work in a non-modular production environment. Free-riding resulted in the removal of a signaling function of price for the difficulty levels of tasks. However, this removal was not sufficient to lead to the catastrophic outcome of zero payoff. In fact, for one measure of efficiency, small teams were more efficient than large teams in the non-modular production and efficiency was higher in the modular production irrespective of team size.

If the two team size levels here are a reasonable approximation to the team size levels in a given firm, here are some implications for managers concerning efficiency: if the production function is restricted to be non-modular, reduce the team size; with no such restriction, always choose the modular production function.

This paper calls for more explanations about some effects of non-modularity (across different team sizes) that offset the dis-incentives mentioned in the management science research and sub-optimality in the computer science literature. We have not directly investigated what prevented the catastrophic outcomes and whether subjects use the contents instead of prices to (at least implicitly) signal the difficulty levels of tasks. We also have not directly investigated whether and how open contents facilitate learning. But the data showed that spillover was significantly higher in the non-modular production. The exact mechanisms about how production costs can be lowered due to spillover might offer a promising path for future research.

CHAPTER IV

Using Uncensored Communication Channels to Divert Spam Traffic

4.1 Introduction

We all receive spam; we all resent it. Justice Potter Stewart, were he alive, would know it when he saw it. Nonetheless, it is hard to find a consensus definition of spam. Some want to include all unsolicited commercial email; others include unsolicited bulk email; others distinguish between deceptive, informative or malicious email. We should not be surprised, then, that it is also hard to find systematic analyses of "the spam problem", when there are so many notions of what spam is.

Our goals are twofold. We want to identify a particular (but prevalent) subspecies of spam, analyze its ecology, and propose a mechanism that may increase social welfare substantially by modifying the flows of this type of spam. We also hope to lay groundwork for systematic modeling of spam, and the consequent development of solutions that are effective because they address systematic features of the problem.

We define spam as *bulk, unsolicited, commercial email*; that is, effectively identical (but usually randomly disguised) messages sent unsolicited to large numbers of recipients with the goal of inducing a willing, mutually-beneficial purchase by the recipients. With this definition (we will call it "spam" for convenience, but it's merely one subspecies) we rule out malicious bulk unsolicited email (e.g., email carrying a virus payload); we rule out deceptive email (e.g., "phishing" messages that attempt to trick recipients into revealing valuable personal information such as bank passwords); and we rule out email (though *initially* unsolicited) sent to a mailing list, from which one could unsubscribe. What we rule out is not insignificant; we just take our definition as a starting point and leave the study of other email problems for future research. We do document that commercial spam is the most prevalent form. And we have analyzed how some of our results change when the proportion of malicious and deceptive email changes.

Defined as we have done, spam is an instance of a differently-named, well-known phenomenon: advertising. Using the less-pejorative moniker "email advertising" might give us a good start on a thoughtful, systematic consideration; certainly, it might help us recognize that at least this type of spam is not per se evil or morally deficient (though, as with any advertising, some population subgroups might conclude that the products advertised might fail that group's morality test). Nonetheless, we will use "commercial spam" or just "spam" for short, because we relish the powerful affective response the term receives, and the opportunity to puncture the pejorative bubble it engenders.

To develop a systematic analysis of (non-deceptive, non-malicious) commercial spam, we need grounding principles. We find that surprising insights follow from adopting just two familiar, simple economic principles:

Revealed preference There is a non-trivial *demand* for the receipt of spam email.

Rational choice Spam purveyors will send spam messages to whomever, wherever, whenever, as long as the expected benefits exceed the expected costs.

We expect that only the first principle will raise many eyebrows at first, but we find that the second principle consistently has been half-ignored in most prior literature on “the spam problem”.

First, demand. Spam is not costless to generate or deliver, despite casual claims to the contrary. It is true that replication and transport costs are extremely low, compared to non-digital advertising channels. But there are a number of other costs: marketing and contracting costs with advertisers, content creation costs, content disguising costs (to get past technological filters), distribution technology costs (most spam is now sent out by virus-created spambots running on many machines not owned by the spam provider; these botnets need to be continuously regenerated, which requires developing new viruses to distribute, among other things). There may also be the cost of expected legal penalties. Given the non-zero costs of providing a spamming service, and with our scope limited to just commercial spam, from which the benefit to the sender is the inducement of willing purchases by recipients, we must conclude the following: by revealed preference, there is a non-trivial demand for the receipt of spam email. Some consenting adults must be purchasing enough Rolex knock-offs and counterfeit products to pay the spammer’s costs.

While the revealed demand could encompass some spurious demand induced by malicious or deceptive ads (e.g., for fake Viagra), some portion of the revealed demand is likely to be real. Few buyers will believe that a $50 Rolex is authentic.[1] In any case, we do not rule out spurious demand. Rather, we simply analyze the potential of our proposed mechanism to reduce non-spurious demand for bulk email advertising. We do not claim that this mechanism is likely to also eliminate deceptive ads from the inbox.

To motivate and clarify our scope, we present some informal evidence. Such evidence is consistent with our claim that there is non-trivial demand for much spam: *Cranor and LaMacchia* (1998) show that the largest fraction of spam content is com-

[1]There may be a deeper issue for some misleading ads: from a neutral social welfare perspective it may not be appropriate to treat some misled demand as spurious. For example, inert imitation Viagra may provide desirable (placebo) effects simply because people think it works.

mercial advertising for products hard to find through other advertising channels. *Sophos* (2005) finds that this pattern continues; for example, in 2005 medication spam constitutes around 40% of all spam, and adult content for another 10-20%. *Evett* (2006) estimates that product spam constitutes around 25% of all spam, and adult content for another 19%.[2] We expect there will always be significant demand for "push" advertising in addition to "pull" (search-based) advertising.[3][4]

Recognizing that *some* recipients want to read spam, while many others evidently do not, we immediately see that one opportunity for social welfare improvement is to find a way to match commercial spam to those who want it, and not to those who do not. The latter email readers would benefit, and spam senders would also benefit by not incurring the costs of sending to people who will not purchase.

As a corollary, we expect the willing recipients of commercial spam to benefit as well: if spammers can find a way to send to those who are interested in receiving the advertisements, then they can reduce their costs *and* increase the information content and quality in their ads, to the benefit of those who want the commercial information. Consider: Yellow Pages are a fairly successful bulk advertising medium because the ads are generally viewed only by those who want to see them, and the advertisers have the incentive to make the ads clear and informative, giving the viewers the information they desire. Spammers in contrast incur substantial costs to disguise the information in their ads so that filters cannot easily remove the ads from the email stream. But then the readers who do want the information so they can make

[2] *Evett* (2006) compiles his statistics from sources that include Google, Brightmail, Jupiter Research, eMarketer, Gartner, MailShell, Harris Interactive, and Ferris Research.

[3] This is evidenced by the multiple media for advertising that co-exist in equilibrium (Yellow Pages, local newspapers, billboards, broadcast TV and radio ads, bulk unsolicited commercial surface mail ads, etc.). Many products using commercial spam advertising do not want a durable, public presence. If they are moving their web sites to new domains frequently, they need a communication channel through which to disseminate each new, temporary location. Indeed, we observe cases in which the links for some domains selling medications expired in Google's index well before Google got a chance to renew the links. For example, *MessageLabs* (2005) shows that about 30% of spam domains expire within 24 hours.

[4] *Hann et al.* (2008), in modeling avoidance behavior by marketing recipients, also model spam as advertising for which there is non-zero demand.

a purchase are confronted with uninformative, low-value ads.

The second principle we offer as a foundation for systematic analysis of the spam ecology is that spammers are for the most part rational businesspeople, and they will send ads when the expected benefit to them exceeds the expected cost. What insight do we obtain from this unsurprising observation?[5] We answer, first, indirectly: most other authors addressing spam have focused on proposals to raise the cost of spamming as a way of reducing the amount of spam produced. This approach is principled, but incomplete. An equivalent reduction in the benefits of spamming (e.g., by inducing those who want spam to read it in a different channel) should have the same (qualitative) incentive effect. If spam were flood waters, the existing solutions are in the spirit of building stronger levees to raise the river banks, instead of diverting the flood waters using a floodway. Both might properly belong in an effective flood management policy.

We build on these two principles to construct a model for commercial spam that includes advertisers, spam service providers, email service providers, and mail recipients who have heterogeneous tastes for receiving spam.[6] See Figure 4.1. We then introduce a simple but novel mechanism motivated by the two principles above: an uncensored (open) communication channel through which spam will be accepted without filtering or other attempts to block. Such a channel could be as simple as a standardized mail client folder that would accept all appropriately labeled messages.[7] See Figures 4.2 and 4.3. Our conjecture is that if well-designed, then under some circumstances the introduction of an uncensored channel could result in substantial

[5]We know, of course, that not every decision, in every circumstance, satisfies a test for decision-theoretic rationality. We only require that costly business decisions in general follow from reasonable comparisons of benefits to costs.

[6]In our current model we focus on the preferences and behaviors of recipients, spammers, and advertisers. We use a reduced-form, non-adaptive representation for email service providers.

[7]On a practical level, the sender chooses whether to send to the censored or the open channel (or both). When sending to the open channel, the sender does not disguise content, and adds a tag that indicates the message should be delivered to the open channel. If sending to the censored channel, the sender does not tag the message, and in fact may expend some effort to disguise the content.

self-segregation by spammers, with email advertisements mostly targeted at the open channel, and much less at the traditional (censored) channel. See Figure 4.4.

There should be little dispute that if users could implicitly opt-in for commercial spam by creating an uncensored folder, the spammers would send mail to that channel. But why would they stop sending (or at least send less) to the censored channel? Our hypothesis is that if enough of the latent demand for purchasing spam-advertised products is reached through the uncensored channel, then the remaining commercial benefits obtainable from also spamming the censored channel may fall sufficiently low that they no longer justify the incremental costs.[8] In our formal model below we show one set of conditions sufficient to guarantee this result.

There is another reason for spammers to keep sending to the traditional censored channel: persuasion. We are assuming that recipients know if they want to periodically purchase based on spam advertisements, and thus can make an ex ante rational choice about which channel to read. This situation is known in the literature as informative advertising[9]: consumers know they want information (price, location, etc.) about particular products, and seek out informative advertising to obtain the information they need. But there is another category: persuasive advertising, intended to convince consumers to buy products they previously did not realize they wanted. Since these ads are aimed at consumers who might generally opt out of the open channel, it would do little good to send them to the open channel (which these previously uninterested customers shun), so the persuasive advertiser will generally go to where the unpersuaded are (the censored channel). Persuasion, however, comes at the cost of being filtered more easily because of the less disguised content. If the open channel

[8]One reason the benefits in the censored channel might drop is that if users looking for unsolicited ads turn first to the better organized and more informative open channel, the level of demand for products advertised with less informative messages in the open channel may fall sufficiently that the expense of sending to the censored channel — and spending to get around the filters — is no longer worthwhile.

[9]See especially the section under the sub-heading “Is advertising used to inform or persuade?” on p. 28 of *Taylor* (1934).

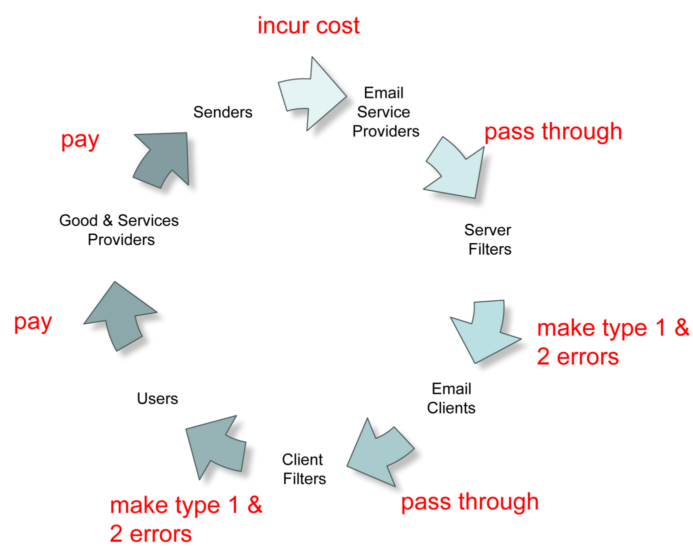


Figure 4.1: Stakeholders In An E-Mail Ecosystem.

Figure 4.2: An Hypothetical Open Channel.

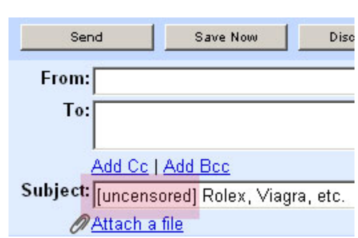


Figure 4.3: An Hypothetical Tag.

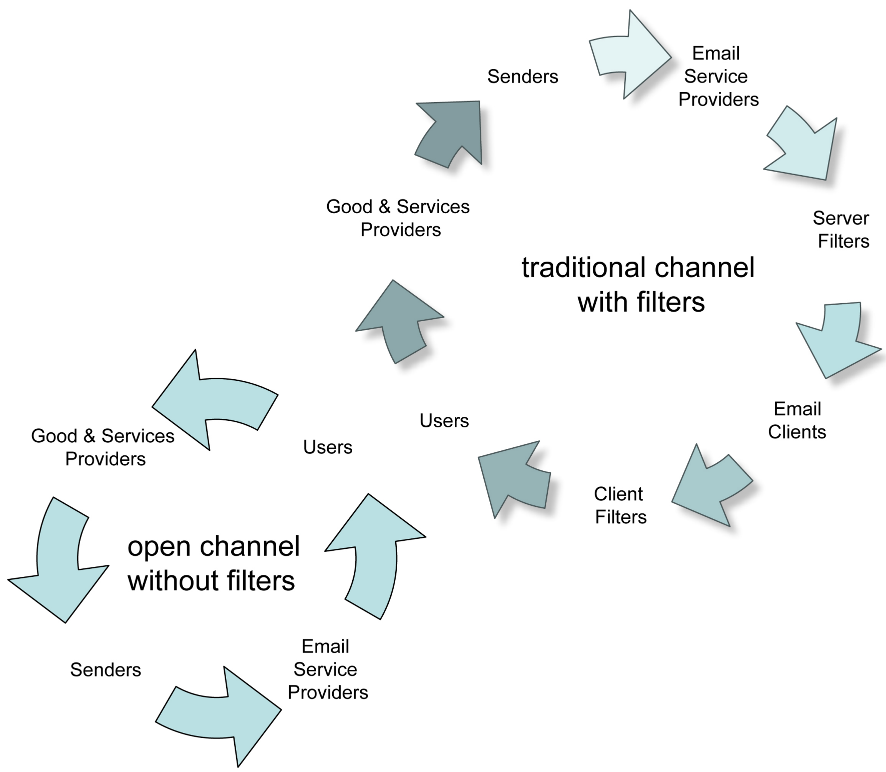


Figure 4.4: Separating The Demand For And Supply Of Bulk Unsolicited Commercial Advertising.

does not make persuasion in the censored channel *easier* than when there is only the censored channel, the omission of persuasive advertising is not *necessary* fatal (see discussions right before Proposition IV.6).

Recall also that if spammers do choose to target the open channel, then we expect that they will also stop dissipating resources on unproductive efforts to disguise the informative content of their messages. Then those who wish to receive email advertisements will benefit from the higher quality (informativeness). This increase in informativeness, in turn, likely would induce a larger number of consumers to *want* to receive commercial spam.

We construct a model so that we may formally identify conditions under which the conjectures above hold true (and conditions under which they do not). Our main results are to characterize the degree to which spam will be shifted to the open channel, and to demonstrate that under reasonable assumptions all parties benefit from the introduction of an open channel, so that it constitutes a Pareto improvement.

4.2 Prior approaches to spam

To date, most research focuses on reducing spam generally, usually through policy, technical or market mechanisms that raise the cost of sending spam. Before we detail our model of a mechanism that diverts spam to those who want it, and away from those who don't, we review other approaches.

4.2.1 Technological

Technological solutions have gained some partial success but the results are far from satisfactory even though they have been implemented for some time. The proposals include rule-based, Bayesian, and community ("collaborative") filtering, disposable identities using extended email addresses (*Bleichenbacher et al.*, 1998), DomainKeys Identified Mail (*Perez*, 2005), Sender ID or Sender Policy Framework

(*Crocker*, 2006)[10], challenge-response (*Dwork and Naor*, 1993; *Laurie and Clayton*, 2004), whitelists, and blacklists. See *Cranor and LaMacchia* (1998) for an overview of these ideas (though not of course of the more recent specific proposals).

There is a fundamental problem with technological systems: they typically rely on the cost to spammers of devising technological workarounds. If the cost is high enough, the net benefit of spamming will be insufficient and the quantity of successful (delivered) spam will fall. However, the costs of technological workarounds fall rapidly, as technology becomes exponentially cheaper and as algorithmic solutions to hard computational problems rapidly improve. Thus, as the workaround cost falls, the technological barrier becomes less effective and spam delivered increases. This fundamental cost dynamic creates a need for ongoing investment to create improved anti-spam technologies. While an "arms race" may not be the first-best solution, we have not seen feasible methods to avoid this cycle, given the inevitable and rapid decline in technology costs. Certainly, though some of the cost has been shifted to ISPs and mail service providers, it appears that the social cost of spam has been increasing, not decreasing, despite the proliferation of technological fixes.

4.2.2 Legal

Legal rules are another approach to spam reduction. The U.S. CAN-SPAM act required a formal recommendation from the Federal Trade Commission regarding the establishment of a do-not-spam registry similar in the spirit of the do-not-call and do-not-fax registries created pursuant to the Telephone Consumer Protection Act of 1991. Although The FTC recommended against the creation of the list, other CAN-SPAM rules took effect 1 January 2004. However, legal solutions alone are, and likely will remain incomplete. First, to avoid prohibiting desirable email communications, legal rules generally include safe harbor provisions guaranteeing the permissibility of email

[10] As of now, spam-sending domains are ironically the biggest users of SPF tags (*MXLogic*, 2005)

exhibiting certain characteristics. It is generally difficult or impossible to prevent spammers from composing their messages so that they exhibit these characteristics, thus creating a safe harbor for a large and probably growing quantity of spam. Second, legal jurisdiction over spam-distributing organizations is a crucial problem: spammers can easily change their locations to other countries.

4.2.3 Markets

Some proposals based on economic incentives have been gaining attention. These share an important feature with our approach to the problem: they typically are based on a presumption that users have heterogeneous values for receiving various email messages.

In an experimental investigation of email stamps as a price for obtaining a recipient's attention, *Kraut et al.* (2005) found that charging causes senders to be more selective and to send fewer messages. This method, however, requires non-spammers to pay a price as well. *van Zandt* (2004) examines the design of an optimal tax that minimizes exploitation of attention through information overload. Various email stamp systems have been or are about to be implemented.[11] *Loder et al.* (2006) propose an attention-bond mechanism in which a sender deposits a monetary bond to a third-party agent, to be released only if the receiver tells the agent to do so. Both *Loder et al.* (2006) and we recognize hetereogeneous valuations of mail messages; they provide an incentive that increases spammer costs, while we provide an incentive that reduces spammer benefits.

Payment systems require substantial infrastructure for full implementation. The

[11] Two of the world's largest providers of e-mail accounts, America Online and Yahoo!, announced in early 2006 that they would give preferential treatment to messages from companies paying from 1/4 of a cent to a penny each. An email stamp system was already implemented in Korea in 2003. Daum Corporation, the largest portal in Korea, charges about 0.8 cents to the senders who send more than 1000 messages per day. Fees scale downwards if senders are ranked lower than the biggest senders or more users rate the email as useful. Data cited by *Kraut et al.* (2005) indicate that spam was reduced by about 40% from its peak in a half-year period around the implementation.

infrastructure necessary for widespread micropayment is lacking, and for successful adoption into a service exhibiting network effects, such as email, it is likely necessary that there be early widespread, not incremental, adoption, which is difficult to socially engineer. Also, there is a norm of free email service. Legitimate senders may resist paying for outgoing email more strenuously than is strictly justified if they took into account the system benefits to their recipients.

4.3 Theory

In our brief review of other approaches to spam we highlighted one common feature: they are generally based on raising the costs of spamming, not on reducing the benefits. In addition, technological and legal methods (and some market methods, but less so) implicitly assume that certain mail (or mail senders) are uniformly undesirable; that is, they ignore heterogeneity in recipient preferences. In this section we present a model of the two-sided market for commercial spam, in which product sellers pay spammers to deliver advertisements to email recipients, some of whom in turn willingly choose to purchase the advertised products.[12] We then analyze the effect of introducing an open (i.e., uncensored) channel. The open channel approach is designed to lower the benefits to spammers of sending mail to all recipients, and works only and precisely because recipient preferences are heterogeneous: viz., some recipients want to receive email advertisements.

4.3.1 Mail Types

Mail types coincide with senders' types. Such types are defined by two attributes: mass or targeted mail, and solicited or unsolicited.

The first attribute is mainly a cost attribute of sending. The content creation cost

[12] The email market is a typical problem of two-sided markets (e.g., *Rochet and Tirole* (2003), *Parker and Alstyne* (2005)), which is closely related to the chicken-and-egg problem. Roughly speaking, the number of senders affects the number of recipients, and vice versa.

per copy of mass mail is much lower than that of targeted mail.[13] [14] Also, because of information asymmetry of each recipient's preference for spam, by definition, mass-mail senders' best strategy is to randomize recipients' addresses.

The second attribute is mainly a cost attribute of blocking. As mail is considered solicited for our purpose, even if it is initially unsolicited, if one could easily unsubscribe (block) oneself from such mailing lists permanently.

In all, we identify four types of mail, and provide examples:

Unsolicited mass: Viagra and erotic content advertisements.

Unsolicited targeted: Personalized advertisements based on purchase history obtained elsewhere.

Solicited mass: Advertisements from conventional booksellers, non-profit fundraisers, and other legal and less socially objectionable purveyors.

Solicited targeted: Personal correspondence.

Unsolicited mass mail constitutes the bulk of the unwanted email for most individuals. We therefore simplify our analysis using this convenient assumption:

Assumption IV.1. *Mail Segregation: Mass-mail senders send only unsolicited mail, and targeted-mail senders send only solicited mail.*

Henceforth, when the context is clear, we refer to unsolicited mass mail senders as senders, and the mail they send simply as mail.

[13] We do not require that it is possible to identify whether a message is mass mail or targeted mail. It is easy to fool general purpose filters, and the recipient often will not know until after incurring the cost of viewing the message.

[14] There has been substantial debate about whether spamming is inevitable because the incremental cost of a spam message is essentially zero. It is clear to us that the cost is not zero: costs of disguising, costs of obtaining valid email addresses, costs of legal proceedings, and bandwidth costs all likely increase with the number of spam messages sent. If the spammer is using a spambot farm of compromised machines to provide "free" processing and bandwidth, there will be costs of writing the viruses that carry the spambot payloads: the more spam messages to send, the more machines need to be compromised. See *Hann et al.* (2006) for recent estimates of the non-zero incremental costs of spamming.

4.3.2 The Recipients' Problem

Assume that for unsolicited mass mail, some individuals want to receive a fraction $1-\epsilon$. The value $\epsilon \in [0,1]$ increases if there are more undesirable properties with unsolicited mass mail such as phishing and malicious content. We assume there are two types of recipient: "high" and "low". Only high-types desire unsolicited mass mail (that is, have some demand for the goods advertised in such mail). We define a variable to indicate demand for unsolicited mail: $w_r : \{w_{\bar{r}} = 1, w_{\underline{r}} = 0\}$. There is a large number of high-type ($\bar{r}$) recipients indexed by $\bar{r}$ on the interval $[0,1]$ according to a probability distribution $\psi_{\bar{r}}$. The corresponding index for low-type recipients is $\underline{r}$ distributed according to $\psi_{\underline{r}}$. Recipient types are exogenous. We assume recipients of a given type have the same budget for spending on advertised goods, and normalize this amount to w_r. They buy goods from ads in the channel that offer the lower average price, where p^j is the average price offered by ads in channel j. We later model how recipients respond to an advertisement based on how informative or transparent it is. Whether mail (desired or undesired) is received depends on the filtering technology employed by the email service provider. We model this below, but for now simply refer to mail that gets through as "unfiltered" and mail that does not as "filtered".

In the censored channel, filtering technology is designed to block unsolicited mass mail, but it does so imperfectly. Each sender knows that the filter has a strength of $f^c \in [1, \infty)$ for unsolicited mass-mail. The filter strength is simply the inverse of the fraction of mail that gets through the filter. By definition there is no filtering in the open channel, $f^o = 1$.

Sender s can make an effort to disguise its content to reduce the filter's success rate. We let sender s choose a transparency level, $t_s^j \in [\frac{1}{f^j}, 1]$, for mail sent to channel j, where t_s^j is a multiplicative factor adjusting the filter strength. If $t_s^j = 1$, the mail is transparent with no disguise at all and the effective filter strength is the technological strength f^j. If $t_s^j = 1/f^j$, the effective filter strength is one, which is to say, all content passes through unfiltered. Disguising is costly; there is no effort made to disguise content in the open channel.[15]

Denote N_r^j as the volume of mail sent to recipient r in channel j. Essentially, it is the mail sent averaged across all recipients in j. R_r^j is the number of high-types using channel j; R^j is the total number of recipients who choose to use channel j. Then the unfiltered portion that actually reaches recipient r is denoted by $n_r^j \equiv \frac{N_r^j}{t^j f^j}$, where t^j is the weighted average of transparency levels in channel j.

We define $\kappa_r^j = 1$ if recipient r uses channel j, zero otherwise. To build a tractable model, we make another assumption to rule out the *unlikely* scenario that no one is using the existing email channel:

Assumption IV.2. ***Channel Essentiality****: The censored channel is essential so that every recipient uses it. That is,* $\kappa_r^c = 1$.

Let us now state the recipient's problem formally. Given other variables, recipient r makes a binary choice of whether to opt into the open channel, $\kappa_r^o \in \{0, 1\}$, by maximizing:

$$U_r(\kappa_r^o) \equiv U_r(v_r^g(\kappa_r^o), v_r^I(\kappa_r^o), v_r^{II}(\kappa_r^o)) \tag{4.1}$$

U_r is increasing in the first argument, and decreasing for the rest. The first argument is the volume of advertised goods consumed, which is given by total spending divided by price (paid to the advertiser indexed by a) in the channel with the lower price (and which is subscribed to by the recipient):

$$v_r^g = \max_j \{\frac{\kappa_r^j w_r}{p_a^j}\}^{16}, \tag{4.2}$$

[15] By definition of the lower bound of t_s^j, $t_s^o = 1$ because $f^o = 1$ implies that the upper and lower bounds coincide.

[16] We simplified the problem from an equivalent but more explicit formulation: Recipient r chooses $\kappa_r^o \in \{0, 1\}$ and $\sum_j v_r^{g,j}$ to maximize $U_r(\kappa_r^o, \sum_j v_r^{g,j}|\cdot) \equiv U_r(\sum_j v_r^{g,j}, v_r^I, v_r^{II})$ $s.t.$ $\sum_j \kappa_r^j p_a^j v_r^{g,j} = w_r$.

which is zero for low-type recipients since $w_{\underline{r}} = 0$.

The second argument gives the Type I errors (unwanted mail that is received):

$$v_r^I = \sum_{j \in \{o,c\}} (1 - w_r + w_r \epsilon) \kappa_r^j \frac{N_r^j}{t^j f^j}. \tag{4.3}$$

When a recipient is a high type ($w_r = 1$), this is the fraction ϵ of unsolicited mail the high type does not want to receive (summed across the channels to which she subscribes). For a low type, this is all unsolicited mail received.

The third argument gives the Type II errors (wanted mail that is filtered out before delivery):

$$v_r^{II} = \sum_{j \in \{o,c\}} (1 - \epsilon) w_r \kappa_r^j N_r^j (1 - \frac{1}{t^j f^j}), \tag{4.4}$$

which is zero for low-type recipients since $w_{\underline{r}} = 0$. There is no filtering in the open channel, so for high types this is the fraction of desirable unsolicited mail $(1 - \epsilon)$ that is filtered out of the censored channel.

4.3.3 The Senders' Problem

There is a large number of senders indexed by s on the interval $[0, 1]$ according to a probability distribution ψ_s. The total cost function for sender s is $C_s(N_s^o, N_s^c, t_s^c) \equiv c_s^o N_s^o + c_s^c N_s^c + d(t_s^c)$. N_s^o and N_s^c are the email volumes in the open and censored channels. t_s^c is the transparency of the mail sent to the censored channel. We assume:

- Constant returns to scale in each volume cost: $\frac{\partial C_s}{\partial N_s^c} = c_s^c > \frac{\partial C_s}{\partial N_s^o} = c_s^o > 0$[17]. Note that c_s^c and c_s^o are constants.

[17] Rather than having a zero marginal sending cost ($\partial C_s / \partial N_s^j$) as commonly asserted, spammers incur cost to renew technologies, which depreciate quickly, to generate spam. For example, zombies (i.e., home computers hijacked by crackers) are consistently destroyed by anti-virus software, so spammers must continuously develop and distribute new viruses to capture new (temporary) zombies. Zombies are responsible for relaying more than 60% of the world's spam (*Sophos*, 2005). One could have used a step function to model the cost function but a smooth function would approximate a step function when the number of zombies increases.

- Negative transparency (positive disguise) cost: $\frac{\partial C_s}{\partial t_s^c} < 0$

On the revenue side, senders are price takers. Advertisers pay them for solicitations. Let p_s^j be the advertising charge per disguised email *reaching* the users in channel j[18,19].

Given other variables, sender s chooses (N_s^o, N_s^c, t_s^c) to maximize:

$$\pi_s(N_s^o, N_s^c, t_s^c) = p_s^o N_s^o + \frac{p_s^c N_s^c}{t_s^c f^c} - c_s^o N_s^o - c_s^c N_s^c - d(t_s^c) \tag{4.5}$$

$$\text{s.t. } t_s^c \in [\frac{1}{f^c}, 1], N_s^o, N_s^c \geq 0 \tag{4.6}$$

Next we state the solutions to the above maximization problem:

Result IV.3. The best responses of sender s are:

$$N_s^o > 0 \iff p_s^o \geq c_s^o \tag{4.7}$$

$$N_s^c > 0 \iff \frac{p_s^c}{t_s^c f^c} \geq c_s^c \tag{4.8}$$

$$t_s^c \begin{cases} = 1 \\ \in (\frac{1}{f^c}, 1) \\ = \frac{1}{f^c} \end{cases} \iff \frac{-E_{C_s, N_s^c}}{E_{C_s, t_s^c}} \begin{cases} < \\ = \\ > \end{cases} 1, \tag{4.9}$$

where E_{C_s,N_s^c} and E_{C_s,t_s^c} are elasticities.

Proof. See Appendix C. □

[18]In practice, there is a volume discount (that might, for instance, be due to diminishing likelihood to respond). For instance, Send-Safe is a service spammers offer to advertisers. One pricing scheme asks for US$125 per 1 million credits (possibly a proxy of $\frac{N_s^c}{t_s^c f^c}$) when an advertiser pays for 0.4 million credits. The price drops monotonically to US$10 per 1 million credits when an advertiser pays for 300 million credits. This pricing scheme is available at http://www.send-safe.com/send-safe.html, accessed 29 March 2009 (though the page appears to have last been updated in 2006).

[19]Whether the price is charged per delivery or per click does not affect the main results of the model, it is largely a normalization issue.

Notice that the marginal revenues of sending N_s^o and N_s^c are p_s^o and $\frac{p_s^c}{t_s^c f^c}$. When the marginal revenue of channel j is strictly less than the marginal cost, sender s does not send any to channel j. Else, sender s makes some economic profit because in channel j the marginal revenue is weakly greater than the marginal cost in a given channel. To increase the total revenue ($\frac{N_s^c p_s^c}{t_s^c f^c}$) in the censored channel by the same amount, a sender could either adjust N_s^c or t_s^c by the same amount, depending on this ratio of elasticities $\frac{-E_{C_s,N_s^c}}{E_{C_s,t_s^c}}$.

4.3.4 The Advertisers' Problem

There is a large number of advertisers indexed by a on the interval $[0,1]$ according to a probability distribution ψ_a. Advertiser a's total cost derives from the production of goods sold, and from the advertising for them.

Let θ^j be the probability that an advertisement in channel j leads to a purchase, and n_a^j is the number of messages delivered on behalf of advertiser a (whereas N_a^j is the number sent, the difference being due to filtering). Production cost $C_a(\sum_j \theta^j n_a^j) \equiv c_a \cdot \sum_j \theta^j n_a^j$, exhibits constant-returns-to-scale technology. c_a is the constant marginal production cost. $\theta^j = \theta(t_a^j, \frac{R_{\bar{r}}^j}{R^j})$, where t_a^j is the transparency level of email in channel j associated with advertiser a, and $\frac{R_{\bar{r}}^j}{R^j}$ is the ratio of high-type recipients in channel j. θ^j is increasing in both arguments; it equals zero if $\frac{R_{\bar{r}}^j}{R^j} = 0$.

Advertising cost, $\sum_j p_s^j n_a^j$, is linear. Recall that p_s^j is the marginal advertising charge in channel j that is paid to senders.

For each p_s^j paid, advertiser a collects expected sales revenue equal to the price paid by ad recipients *cum* consumers, p_a^j, times the probability of making a sale in channel j, θ^j.

Given other variables, advertiser a chooses (n_a^o, n_a^c) to maximize:

$$\pi_a(n_a^o, n_a^c) = \sum_j (p_a^j \theta^j (t_a^j, \frac{R_{\bar{r}}^j}{R^j}) - p_s^j) n_a^j - c_a \cdot \sum_j \theta^j n_a^j \tag{4.10}$$

$$\text{s.t. } n_a^j \geq 0 \tag{4.11}$$

Result IV.4. The best responses of advertiser a are:

$$n_a^c > 0 \iff \theta^c c_a + p_s^c \leq \theta^c p_a^c \tag{4.12}$$

$$n_a^o > 0 \iff \theta^o c_a + p_s^o \leq \theta^o p_a^o \tag{4.13}$$

Proof. See Appendix D. □

This result implies that the volume requested should be zero in both channels if the marginal cost exceeds the marginal benefit in each channel, and that the volume requested in channel j should be strictly positive when the marginal markup is positive. The marginal markup is the marginal sale price (p_a^j) minus the marginal cost of a sure response ($\frac{p_s^j}{\theta^j}$) and marginal production cost (c_a).

4.3.5 Equilibrium

4.3.5.1 Competitive Equilibrium

By assuming atomistic, price-taking recipients, advertisers and spam senders (which can be justified for the latter two by an assumption of free entry), we have the conditions for a competitive equilibrium. Using a hat symbol to denote equilibrium values, a competitive equilibrium by definition satisfies the following:

- the goods and services market is cleared:

$$\int_{\bar{r}\in[0,1]} \hat{v}_{\bar{r}}^g \psi_{\bar{r}}(\bar{r}) d\bar{r} + \int_{\underline{r}\in[0,1]} \hat{v}_{\underline{r}}^g \psi_{\underline{r}}(\underline{r}) d\underline{r} = \sum_j \hat{\theta}^j \left(\int_{\bar{r}\in[0,1]} \hat{n}_{\bar{r}} \psi_{\bar{r}}(\bar{r}) d\bar{r} + \int_{\underline{r}\in[0,1]} \hat{n}_{\underline{r}}^j \psi_{\underline{r}}(\underline{r}) d\underline{r} \right) \tag{4.14}$$

- the mail market is cleared:

$$\int_{\bar{r}\in[0,1]} \hat{n}^j_{\bar{r}}\psi_{\bar{r}}(\bar{r})d\bar{r} + \int_{\underline{r}\in[0,1]} \hat{n}^j_{\underline{r}}\psi_{\underline{r}}(\underline{r})d\underline{r} = \int_{a\in[0,1]} \hat{n}^j_a\psi_a(a)da = \int_{s\in[0,1]} \frac{\hat{N}^j_s}{\hat{t}^j_s f^j}\psi_s(s)ds \tag{4.15}$$

- the profits of senders and advertisers are maximized:

$$\pi_s(\hat{N}^o_s, \hat{N}^c_s, \hat{t}^c_s) = \max_{N^o_s, N^c_s, t^c_s} \pi_s(N^o_s, N^c_s, t^c_s) \tag{4.16}$$

$$\pi_a(\hat{n}^o_a, \hat{n}^c_a) = \max_{n^o_a, n^c_a} \pi_a(n^o_a, n^c_a) \tag{4.17}$$

- the zero economic profit conditions are satisfied:

$$\pi_s(\hat{N}^o_s, \hat{N}^c_s, \hat{t}^c_s) = 0 \tag{4.18}$$

$$\pi_a(\hat{n}^o_a, \hat{n}^c_a) = 0 \tag{4.19}$$

- the utility of each of the high and low-type recipients is maximized:

$$U_{\bar{r}}(\hat{\kappa}^o_{\bar{r}}) = \max_{\kappa^o_{\bar{r}}} U_{\bar{r}}(\kappa^o_{\bar{r}}) \tag{4.20}$$

$$U_{\underline{r}}(\hat{\kappa}^o_{\underline{r}}) = \max_{\kappa^o_{\underline{r}}} U_{\underline{r}}(\kappa^o_{\underline{r}}) \tag{4.21}$$

4.3.5.2 Aggregation

By homogeneity, integrating over all agents of the same type gives a commonly used result: the aggregate value is equal to the average value (i.e. $\int_{k\in[0,1]} \hat{z}^j_k h(k)dk = \hat{z}^j_k \int_{k\in[0,1]} h(k)dk = \hat{z}^j_k$,where h is the probability distribution function of $\hat{z}^j$). In this sense, we justify the use of representative agents for convenience. The values they have chosen are simply the total consumed by the same type of agents in the economy.

The following expression states that the volume of goods consumed by all recip-

Advertising mail volume in		Opt-in is a best response?	
Open channel	Censored channel	High types	Low types
Zero	Zero	Yes and No	Yes and No
Zero	Positive	Yes and No	Yes and No
Positive	Zero	Yes	No
Positive	Positive	Yes and/or No	No

Table 4.1: The Best Responses of Recipients

ients (and the representative high and low type recipients) is equal to the response rate times the unfiltered volume received, requested or sent across all channels. (4.14) and (4.15) give:

$$\sum_j (\hat{v}^{g,j}_{\bar{r}} + \hat{v}^{g,j}_{\underline{r}}) = \sum_j \hat{\theta}^j (\hat{n}^j_{\bar{r}} + \hat{n}^j_{\underline{r}}) = \sum_j \hat{\theta}^j \hat{n}^j_a = \sum_j \hat{\theta}^j \frac{\hat{N}^j_s}{\hat{t}^j_s f^j}. \tag{4.22}$$

4.3.5.3 Nash Equilibria

We first show the following best responses of the recipients. Note in particular that high-type recipients, and only they, will use the open channel if the advertising mail volume sent to the open channel is strictly positive and that sent to the censored channel equals zero.

Result IV.5. If the utility increase with the increase in goods purchased at least offsets the utility decrease with the increase in Type I errors, the best responses of the recipients are listed in Table 4.1.

Proof. See Appendix E. □

The first two rows of Table 4.1 are not very interesting (though necessary to calculate the equilibrium): if no mail is sent to the open channel, it is a matter of indifference to both types of use whether they subscribe to that channel or not. When there is open channel mail, it is not surprising that low-type recipients do not use the open channel because each of the arguments in their utility function can only move in the undesirable directions if they opt-in. For the high-type recipients, it is not immediately clear that they will opt-in for sure because the utility increase due to the increased volume of goods consumed could be offset by the utility decrease due to the increase in Type I and II errors[20].

We now show the only symmetric pure-strategy Nash equilibrium besides the status quo[21]. The status quo in this simultaneous game is a trivial one, which falls into the class of chicken-and-egg problems typical in two-sided markets: no agents use the open channel because no other agents use it. The remaining pure-strategy Nash equilibrium is our main result: the open channel diminishes the volume of unsolicited mass mail in the censored channel to zero, and only high-type recipients use the open channel.

The intuition is simple. Senders' actions can be grouped into four cases: positive or zero volume in each channel. There can be no best response when there is zero volume in each channel because the profit is undefined due to infinite sales prices. If mail is only sent to the censored channel and no recipients opt in for the open channel, this scenario is identical to the status quo. When there is positive volume in each channel, the senders are wasting resources on mail sent to the censored channel because sales could have been made in the open channel as well but with less costs. The only case left is for mail to be sent only to the open channel, which is optimal for the senders when the high types have opted in for the open channel and when the marginal revenue generated is greater than the marginal cost for the senders. Now when senders send only to the open channel, we know from Result IV.5 that the best response for the high types is to opt-in but not for the low-types.

One may wonder if this representative agents model captures the case when every

[20]The readers might worry that a lemon market would emerge where only undesirable email is present in the open channel. One could extend the model to lessen the effects of the lemon problem. For example, one could assume that recipients using the open channel are more cautious. Or there could be messages in the open channel that dissuade (e.g a spammer selling fake Viagra might tell people to not to respond to certain messages that would link to sites that steal one's credit card information.)

[21]The symmetry here refers to same parameters of agents within each type (recipients, senders, and advertisers), which is subsumed in our representative agent modeling.

sender sends only to the open channel, will some advertiser $\widetilde{a}$ benefits from deviating to send some to the censored channel? The answer is no for agents with homogeneous costs because $\widetilde{a}'s$ response rate can't increase.[22] Intuitively, for each mail message $\widetilde{a}$ sends to the censored channel, another sender can always undercut the price advertised in $\widetilde{a}'s$ message by sending an identical message to the open channel with a lower price. The second price is lower because there is no need to disguise the message and the sending cost is cheaper in the open channel. Will the recipients bother to search for the undercutting message in the open channel whenever they see a message, in the censored channel, advertising goods that interest them? Very possibly because the marginal costs of search is very low: the recipients can cut and paste the first message into the search box in the open channel to find an exact match there with a lower price. One could of course argue that the fixed costs of such search skills are high because of learning needed.

Proposition IV.6. Nash: Besides the status quo, the only symmetric pure-strategy Nash equilibrium is: $(\hat{\kappa}^o_{\bar{r}} = 1, \hat{\kappa}^o_{\underline{r}} = 0; \hat{N}^o_s > 0, \hat{N}^c_s \to 0, \hat{t}^c \leq 1; \hat{n}^o_a > 0, \hat{n}^c_a \to 0)$, which exists if $\hat{\theta}^c \hat{p}^c_a < \hat{\theta}^c c_a + c^c_s \hat{t}^c_s f^c$ and $\hat{\theta}^o \hat{p}^o_a = \hat{\theta}^o c_a + c^o_s$. The status quo is Nash if $\hat{\theta}^c \hat{p}^c_a = \hat{\theta}^c c_a + c^c_s \hat{t}^c_s f^c$ and $\hat{\theta}^o \hat{p}^o_a < \hat{\theta}^o c_a + c^o_s$.

Proof. See Appendix F. □

4.3.6 Welfare

When the sales price in all transactions is lowered, the volume of goods sold increases given a fixed expenditure. Equation (4.22) tells us it could mean that the response rate, the mail volume or both has increased. It could also mean that the

[22]For recipients to buy from both channels (justifying $n^c_a, n^o_{\widetilde{a}} > 0$), p^o_a has to be the same as $p^c_{\widetilde{a}}$, which is a contradiction. The reason is that by Results IV.3 and IV.4, and the zero profit conditions, $n^c_a, n^o_a > 0$ implies that $\hat{p}^c_{\widetilde{a}} = c_{\widetilde{a}} + \frac{c^c_s t^c_s f^c}{\hat{\theta}^c}$ and $\hat{p}^o_a = c_a + \frac{c^o_s}{\hat{\theta}^o}$. By cost homogeneity, $c_{\widetilde{a}} = c_a$. If $p^o_a = p^c_{\widetilde{a}}$, we must have $\theta^c > \theta^o$ because $c^c_s \hat{t}^c_s f^c > c^o_s$. $\theta^c > \theta^o$ is not possible because $\frac{R^o_{\bar{r}}}{R^o} \geq \frac{R^c_{\bar{r}}}{R^c}$ and $t^o_s \geq t^c_s$.

response rate becomes so high that the mail volume decreases. Denote the status quo variables when the open channel is absent using $^\infty$ as a superscript[23], we show the latter:

Proposition IV.7. Mail Volume: For the status quo and the other Nash equilibrium in Proposition IV.6,

$$\sum_j \frac{\hat{N}^j_{\bar{r}} + \hat{N}^j_{\underline{r}}}{\hat{t}^j f^j} \leq \frac{\hat{N}^{c,\infty}_{\bar{r}} + \hat{N}^{c,\infty}_{\underline{r}}}{\hat{t}^{c,\infty} f^c} \iff c_a \hat{\theta}^o + \hat{p}^o_s \geq c_a \hat{\theta}^{c,\infty} + \hat{p}^{c,\infty}_s, \tag{4.23}$$

$$\frac{\hat{N}^o_r}{\hat{t}^o f^o} \leq \frac{\hat{N}^{c,\infty}_r}{\hat{t}^{c,\infty} f^c} \iff c_a \hat{\theta}^o + \hat{p}^o_s \geq \frac{R}{R_{\bar{r}}}(c_a \hat{\theta}^{c,\infty} + \hat{p}^{c,\infty}_s), \tag{4.24}$$

where $\hat{p}^{c,\infty}_s = c^c_s \hat{t}^{c,\infty} f^c > \hat{p}^o_s = c^o_s$.

Proof. See Appendix G. □

Expression (4.23) states that the mail volume received by *all* recipients is lower than that in the status quo if and only if the total marginal cost *per mail received* (i.e., the sum of marginal costs of production ($c_a\hat{\theta}^o$) and advertising ($\hat{p}^o_s$) per mail received) is higher than the status quo value ($c_a\hat{\theta}^{c,\infty} + \hat{p}^{c,\infty}_s$). For the mail volume to decrease after the implementation of the open channel, the new response rate has to be so high that the increase in the marginal cost of production per mail received ($c_a\hat{\theta}^o - c_a\hat{\theta}^{c,\infty}$) is more than the decrease in the marginal cost of advertising per mail received ($\hat{p}^{c,\infty}_s - \hat{p}^o_s$). See Figure 4.5.

Since $\frac{R}{R_{\bar{r}}} > 1$, (4.24) implies (4.23). When each recipient receives less, the total received is also less (the converse is not true). It is scaled by $\frac{R}{R_{\bar{r}}}$ because the comparison now is between the total marginal costs per mail received by the *high-type recipients* (trivially the low-type recipients receive less because there is no unsolicited mass mail in the only channel they opted in). In the status quo, for every $\frac{R}{R_{\bar{r}}}$ mail

[23] When the open channel is absent, we interpret it as $f^o \to \infty$. When such filter strength is infinitely strong, it is as if there is no such channel for any practical use.

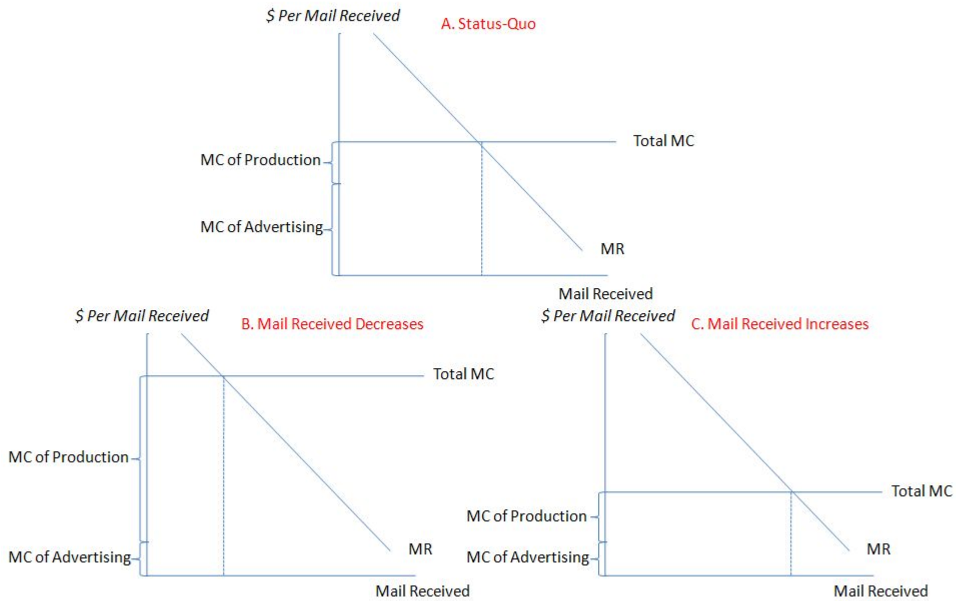


Figure 4.5: Mail Volume Changes Compared to the Status Quo.

received by all recipients, only one is received by the high-type recipients, that is why the corresponding total marginal cost is inflated by $\frac{R}{R_{\bar{r}}}$.

In the following proposition, we prove that in the non status quo Nash equilibrium described in Proposition IV.6, each recipient's utility has not decreased after the roll-out of the open channel because the utility associated with goods does not decrease, and the dis-utilities associated with Type II errors do not increase. Type I errors will not increase for high-type recipients if Proposition IV.7 holds or $\epsilon = 0$. The latter condition ($\epsilon = 0$) is a type of free disposal of unsolicited mass mail in the open channel, which will depend on clutter or handling costs (the cost of disposal itself is vanishingly close to zero). This condition is likely to hold (approximately) if there is a good search engine within the open channel, and if sellers who no longer need to disguise their ads to get past filters will provide information helpful for sorting and filtering ads. Instead of $\epsilon = 0$, we also prove the case in which we require a lower unsolicited mass mail volume than in the status quo.

The structure of the proof is simple. The welfare of the unsolicited mass-mail senders and advertisers will be unchanged because they make zero profit with and without the open channel. The welfare of the recipients could differ. To compare the welfare change for a given recipient when there is an open channel, we compare his or her utility after and before the roll-out of the open channel: $\hat{U}_r - \lim_{f^o \to \infty} \hat{U}_r$.

Proposition IV.8. Welfare: If Proposition IV.6 holds and either Proposition IV.7 holds or $\epsilon = 0$, the welfare of the advertisers, unsolicited mass-mail senders and all recipients will be weakly increased when there is an open channel.

Proof. See Appendix H. □

4.4 Discussion

We emphasize that our proposal is a starting point. Many issues beyond the scope of this analysis need further investigation. We discuss a few here.

It may seem that an open channel is already implemented by the common mail client spam folder. However, a client spam folder is usually the last stage of multi-stage filtering. Most email service providers block some traffic altogether, and only mail that makes it through the first (or first $n-1$) filter(s) are candidates for quarantine in a user spam folder. Thus, to get to that channel, senders already incurred disguise costs.

We mentioned at the beginning that an open channel could be implemented at low cost. Any email service provider could immediately, at minimal cost, offer to let all mail to certain clients pass through with a tag in a header (or even pre-pended to the subject field) that would allow immediate and complete channeling to a separate mailbox; when the email service provider itself provides the mail client (as do online email providers like Gmail and Yahoo!) the open channel inbox could be provided for users that wanted. What is less clear is whether incremental implementation would be successful at drawing senders and readers of unsolicited commercial email into the open channel, or whether widespread, coordinated adoption would be necessary. There are many potential reasons for an email service provider to not implement an open channel currently. Being a multi-product firm, not using the open channel does not imply that adding the open channel will decrease the profit of their email division. However, it might not be implemented simply because it reduces profit in other divisions (such as Google web search that facilitates pull versus the mainly push technology in the open channel).

Would the open channel be flooded with so much more mail — since the cost of sending ads would be lower — that those who want to see ads will incur costs so high to find desired ads that they abandon using the open channel? This is a complicated question, and one largely beyond the scope of this paper. There are good reasons we think this may not happen, however. Since advertisers no longer need to disguise their messages to get into the inbox, they need to only send one message rather than many to guarantee delivery. Further, the advantages of having many more or less identical messages in the inbox may be reduced if recipients can easily find the messages they want and use indexing and finding services to sort through them. Another possibility is the implementation of an expiration feature to the open channel inbox: any messages beyond an expire date are automatically deleted, to reduce clutter. Of course, advertisers will still want to compete with each other for attention, and it is possible they will try to do so by proliferating messages in the open channel. The result on balance cannot be predicted without a more detailed model, and, most likely, some empirical evidence.

We have largely ignored what we call persuasive advertising, namely, advertising that tries to persuade people who did not know that they wanted to purchase anything. These recipients in general will not opt-in to the open channel, and so spammers may still try to reach them through the censored channel. Our conjecture is that if enough demand is shifted to the open channel, and especially if prices for goods advertised there fall due to the lower marketing costs, that demand in the censored channel for goods sold by persuasive spammers may fall enough to discourage this type of advertising, but we have not formally analyzed this. However, if the open channel does reduce the number of ads, the impact on sales of the ads in the censored channel will probably increase, and the open channel will thus make persuasion in the censored channel easier. But we have already argued that the persuaders could face a lower cost competitor in the open channel, which the customers buy from if the search cost to find this competitor is low enough. In other words, the persuaders convince the customers to buy the goods, but the price convinces the customers *where* to buy the good.

4.5 Conclusions

Technical filters and legal rules raise the cost of delivering spam to readers. Costs are borne by spammers (who must develop ever-changing techniques for avoiding filters, etc.), but also by recipients, who spend time doing the difficult filtering and reviewing that cannot be automated, and paying higher costs for goods to cover the marketing expenses. On the other hand, an equivalent reduction in the benefits of spamming (e.g. by moving out spam demanders) should have the same incentive effect. More generally, methods that channel communications more directly to those who want them would lower costs on both sides and be welfare improving.

We formalized this intuition and explored sufficient conditions for all email recipients to be better off with the introduction of an open channel. We show that under these conditions only recipients wanting unsolicited commercial advertisements will use the open channel, and they will benefit from less disguised messages and lower sales prices. In addition, for all recipients the dissatisfaction associated with both undesirable mail received and desirable mail filtered out decreases.

We do not claim that our idea would provide a complete solution to the current spam problem, but of course, no other known and practical methods provide a complete solution either. We do offer a novel new tool that may contribute to a reduction in the flow of spam, and at the same time give advertisers a reason to *increase* the informative content and quality of their ads, to the benefit of those who *do* want to buy goods. Further, if we can tempt a substantial number of consumers who *want* to purchase spam-advertised products into a separate email channel, the purchasing value remaining in the traditional, filtered, or censored channel may drop sufficiently to discourage spammers from using that increasingly unproductive channel.

The important insight we offer, which likely will lead to other, spam-reducing techniques, is to recognize that there is not just a supply curve but also a demand curve for spam. We model the incentives, within the ecosystem of existing spam solutions, to induce both suppliers and demanders to move out of the current censored channel and into the open channel. If customers who want to purchase will benefit from more informative ads in a separate channel, then spam advertisers will benefit from focusing their advertising spending on that channel. This should not be a very controversial idea, but it is, we believe, an idea that has been largely missing from the debate.

There is another illuminating economic perspective on our work: spam is fundamentally a problem that arises when disposal is not free. We know from the First Fundamental Welfare Theorem that unregulated free markets are generally Pareto efficient, but that result requires free disposal. Spam is not free to dispose: it requires time to open and consider. Some types of spam are malicious and may actually cause harm to one's data files or operating system before we can dispose of it.

Our proposal recreates a free market — the open channel — for those who do not want to dispose of spam. It differs from other free-market solutions (e.g. email stamps and bonds for email spam, and Google's AdWords for web spam): The open channel gives recipients the right to receive spam; it removes the right of the email service providers to decide whether the recipients should receive spam. (More generally, the recipients' right to choose the level of censorship is one of the many other possible property right reassignments in the email ecosystem that have been largely unexplored in the literature.) Also, we provide those for whom the disposal costs are sufficiently high (not free) the choice to opt out and participate only in the censored channel. Meanwhile, senders (and spam demanders) do not internalize the disposal costs of uninterested recipients, but the senders nonetheless choose to send less to the censored channel because the average propensity to buy falls as spam demanders move to the open channel.

An open advertising channel is possible at low cost, and it is conceivable that it would make email users at least weakly better off (no worse off) than the status quo. At the very least, this mechanism is fully reversible. If well-designed, an incentive-compatible advertising channel that harnesses the simultaneous forces of demand and supply could significantly reduce the flow of unsolicited bulk commercial email.

CHAPTER V

Conclusions

I studied two economic responses to the challenges of copyright infringements and spam brought about by the birth of the Internet.

I used a tort model to study the inclusion of value-adding vendors who do not need to pay the innovators for the production of open contents. I modeled after the SCO-Linux controversy to include an agent who receives a positive expected payment in intellectual property lawsuits but it is hard for other agents to contract with this agent ex ante. I then analyzed how the litigation between this agent, vendors, innovators and users affects care levels and quantities distributed. The main contributions here are the derivation of some necessary conditions for efficiency and sufficient conditions for inefficiency in the context of open contents. In addition, I derived some necessary conditions for the optimal licensing rules.

Then I reported experimental results on free-riding, efficiency and spillover when large or small teams produce open contents using non-modular or modular production. Price (both pecuniary and non-pecuniary) often drives the allocation of resources. However, it is sometimes difficult to measure the difficulty of a task, even less so by a central authority. If price were used as a measure, it can only be a rather imperfect signal. I documented a case in which price was at times not used to coordinate resources in open contents where production was decentralized. Free-riding, measured as zero price to helpers, was prevalent in the experiment. Large teams were associated with a higher free-riding level than small teams, and free-riding was more severe when large teams work in a non-modular production environment. Free-riding resulted in the removal of a signaling function of price for the difficulty levels of tasks. However, this removal was not sufficient to lead to the catastrophic outcome of zero payoff. In fact, for one measure of efficiency, small teams were more efficient than large teams in the non-modular production and efficiency was higher in the modular production irrespective of team size.

Lastly, I proposed and evaluated an anti-spam mechanism called uncensored communication channel. Technical filters and legal rules raise the cost of delivering spam to readers. Costs are borne by spammers (who must develop ever-changing techniques for avoiding filters, etc.), but also by recipients, who spend time doing the difficult filtering and reviewing that cannot be automated, and paying higher costs for goods to cover the marketing expenses. On the other hand, an equivalent reduction in the benefits of spamming (e.g. by moving out spam demanders) should have the same incentive effect. I formalized this intuition and explored sufficient conditions for all email recipients to be better off with the introduction of an open channel. I showed that under these conditions only recipients wanting unsolicited commercial advertisements will use the open channel, and they will benefit from less disguised messages and lower sales prices. In addition, for all recipients the dissatisfaction associated with both undesirable mail received and desirable mail filtered out decreases.

APPENDICES

APPENDIX A

Strategies for MASTERMIND

This section reviews some strategies discussed in the literature[1]. There is some indication that one can have a different assessment of difficulty level of the same posted game. This is because the number of remaining moves and time needed to find the secret combination varies, which depend on the strategy one uses below.

Stepwise Optimal Strategy

Each guess is optimal in the sense that it is possibly the right answer, that is, it is consistent with all guesses already played. Authors may define the term "consistency" differently. This strategy does not have an expected number of guesses, but it is guaranteed to find the solution in finite time.

A. Exhaustive Search by *Koyama* (1994): In a 4 peg, 6 color game, there are $6^4 = 1296$ possible combinations. The strategy is to generate guesses with a computer in sequence and then rule out the combinations that are inconsistent with the guesses

[1] I borrow heavily from *Kooi* (1986) and *Merelo et al.* (1999) to complete the literature review. I thank Kooi for sending me the working paper.

already played. For instance, if we start with AAAB, the next moves would be AAAC, AAAD... up to AAAF and then AABA, and so on. As we move along, we will be able to rule out combinations that receive no white or black pegs. The advantage of this strategy is that it runs over the search space only once.

B. Random Search by *Strobl* (1998): This approach is similar to *Koyama* (1994) except that it generates combinations randomly. Like the exhaustive search, there are combinations that can be ruled out before being played, but it runs over the search space more than once.

Analytical Strategy

Combinations that are known to be incorrect are played to reduce the search space. Examples:

***Pope* (1995)** In a 4 peg, 4 color game, we can determine what color is used and how many times each color is used by making single-color moves in the first three rows and using a different color each time (e.g. 1st move: AAAA; 2nd move: BBBB; 3rd move: CCCC).

This approach leaves us with five possible scenarios:

- Single-color combination (e.g. AAAA). In this case, we have solved the game by the 4^{th} move.

- 2-color combination with one color used three times and the other used once (e.g. ABBB). This scenario presents $4!/3! = 4$ possibilities. Let's say we learn that the colors are A and B (from the previous three moves). By placing A in a different position each time in the next three moves, we can determine if the combination is ABBB, BABB, BBAB, or BBBA and solve the game by the 7^{th}move.

- 2-color combination with each color used twice (e.g. AABB). There are $4!/2!2! = 6$ possible combinations. Similar to the above scenario, we can use the 4^{th}, 5^{th}, and 6^{th} moves to determine the position of A and solve the game in a maximum of 7 moves.

- 3-color combination (e.g. AABC). In this scenario, we likewise use the next three moves to determine which two slots color A is in. Let's say if color A is in slots 2 and 3, we are left with two possibilities: BAAC or CAAB. We will figure out the positions of B and C in the 7^{th} move and solve the game in 8 moves.

- 4-color combination. This is the most complicated scenario. We can determine which color is in slot 4 by making the 4^{th} move AAAB and, if necessary, the 5^{th} move CCCD.WLOG, let's say color D is in slot 4. Then, in the 6^{th} move we will use the combination, AABD to get either 1, 2, or 3 positional matches. One match means A is in slot 3 and thus leaves us with two possibilities: BCAD or CBAD; Two matches indicates that the combination is either ABCD or BACD; and three matches means it is either ACBD or CABD. In each case, we will be able to identify the positions of the two remaining colors in the 7^{th} move and solve the game in a maximum of 8 moves.

***Knuth* (1976–77)** This is the first paper published on solving MASTERMIND. Knuth's approach allows us to identify the combination after four moves. The expected number of moves is 4.478. The strategy is to choose a guess that minimizes the maximum number of remaining possibilities at each stage. If several guesses satisfy this condition, we will used the one that is a "valid pattern" and receives four black pegs.

Figure A.1 adopts largely from a table in *Koyama* (1994). It shows us the number of possible secret combinations that are consistent with the hints for each possible optimal guess. The first column lists the hints which are combinations of black and

	AAAA	AAAB	AABB	AABC	ABCD
(0,0)	625	256	256	81	16
(0,1)	0	308	256	276	152
(0,2)	0	61	96	222	312
(0,3)	0	0	16	44	136
(0,4)	0	0	1	2	9
(1,0)	500	317	256	182	108
(1,1)	0	156	208	230	252
(1,2)	0	27	36	84	132
(1,3)	0	0	0	4	8
(2,0)	150	123	114	105	96
(2,1)	0	24	32	40	48
(2,2)	0	3	4	5	6
(3,0)	20	20	20	20	20
(4,0)	1	1	1	1	1

Figure A.1: Uneliminated Secret Combination Candidates Consistent with Hints Given to All Possible First Guesses

white pegs. The top row lists five possible choices for an optimal first guess.

The underlined cells in Figure A.1 represent the worst scenario for all possible types of first guesses. According to Knuth, AABB should be played first since it minimizes the worst scenario.

Others In *Bestavros and Belal* (1986), the strategy is based on information theory. The technique is to obtain as much information as possible on the secret combination with each chosen guess, be it on the average or in the worst case. With this algorithm, the secret combination can be found in 3.9 ± 0.5 or 3.8 ± 0.6 average combinations in a 4-peg and 6-color game. This strategy is an improvement on Knuth's approach.

In addition, one can also minimize the number of parts described in *Kooi* (1986). Or one can minimize the entropy as in *Neuwirth* (1982).

APPENDIX B

Instructions to Subjects

The next pages reproduce the instructions to subjects for the non-modular production only[1].

[1]The instructions for the modular production are largely except that there is no longer a group requirement. Whenever person A solves a game (or someone solves a game A has posted), the points A receive will automatically be shown as Period Earnings. The period earnings will be added to the total earnings. In the information panel, the Potential Period Earnings and Group Requirement Achieved cells are no longer there.

1/9/2010 7:15 PM

Experiment Instructions

Welcome. You are about to participate in an experiment that is approximately 2 hours long. You will be paid in cash at the end of the experiment. The payment will depend on the decisions you make. At various points of the instructions you will be instructed to work on short quizzes. When you have finished reading your instructions, raise your hand and the experimenter will come to check your answers before we start the actual experiment. If at anytime you have any questions, raise your hand and the experimenter will assist you. The experimenter will also entertain questions publicly when everyone has finished the instructions.

The instructions are divided into five parts.

I. Standalone Games
II. Working with Games
III. Acquiring Games
IV. Structure of the Experiment
V. How to Use the Software

I. Standalone Games

In a standalone game, there is a combination-maker and a combination-breaker. In each game, the computer will be the combination-maker and you will be the combination-breaker.

For each game, the combination-maker will randomly generate a hidden combination of four pegs using six colors (blue, red, green, yellow, cyan, pink). Colors can be used more than once. For example a combination can be (blue, blue, blue, blue), (red, cyan, blue, blue), (red, blue, green, pink), (green, pink, cyan, yellow), etc. If you have trouble seeing the colors, you can click on **Display Color Numbers** (see Figure 1 on P. 12; Area A).

You have an unlimited number of chances to guess the hidden combination. For each guess, the combination-maker will give you a hint as to how close to the hidden combination you are**. If you have a peg in the correct slot and of the correct color, a black peg will be shown. If you have a peg of the correct color but in an incorrect slot, a white peg will be shown.**

The black and white pegs for each hint refer to any of the four pegs you have chosen, not to any one specific peg. For instance, if the combination is (blue, green, red, yellow), and you guess (yellow, green, blue, cyan), then you will see one black peg and two white pegs (see Figure 2; Area A).

I.1 Reward

For each game solved, the experimenter will give out 10 points. For every 10 points you earn, you will be paid US$1.

There is a group requirement: everyone has to make sure that all **three** of his allotted games in a period are solved either by himself or by other people in this experiment. You will only receive your earnings in a period if everyone solves all his games allotted in that period. In other words, if there is one game that is not solved in a period, none of you will receive your earnings in that period.

The points you earn from solving a game will be shown in the field **Potential Period Earnings.** If **Group Requirement Achieved** becomes “True”, your **Potential Period Earnings** will be transferred to your **Period Earnings**.

Please work on Quiz 1 on P. 8-9 now. Continue with the instructions when you are done.

II. Working with Games

When you are working on a game, there are three courses of action you may take:

II.1 Completing a game
You complete a game by guessing the hidden combination correctly.

II.2 Storing a game to your Private Games Collection
You may click on **Work Later** (see Figure 2; Area B). Doing so will transfer your game, with all of the guesses you have made, into your Private Games Collection. You may resume any of the games from your Private Games Collection at any time during the same period (see Figure 4; Area A).

II.3 Posting a game
You may decide to post a game by clicking **Post** (see Figure 2; Area C). Doing so will transfer your game and all of the guesses you have made into the Public Pool (see Figure 3; Area A).

The Public Pool:

The Public Pool is a collection of games that are <u>visible to all</u> people in this experiment.
Games in the Public Pool can be <u>viewed and cloned</u> by any people in this experiment. When a person clones a game, an exact copy of the game with the history of moves and the same hidden combination is transferred to the person. This person can work on this clone and take any of the three courses of actions listed above.
Games in the Public Pool can be cloned multiple times by multiple people.
When the original game <u>or any clones</u> of it is completed, all clones and the original become void and are no longer able to be worked on.

<u>If a person clones and solves your game, you will be awarded the number of points the game was worth, just as if you finished it yourself. However, when you post a game you can choose the amount of commission you wish to pay another person for solving your game.</u> This number of points will be transferred from your account to his upon his completion of the game. For instance, if you post a game worth 10 points and offer a commission of 4 points you will receive 10 points when this game is solved by another person. Four of these points will be given to the person who solves the game as commission. Thus, you earn 6 points and the other person earns 4 points

Once your game has been posted, there is no way to control the circulation of it. People may clone many copies of your game. You can, however, grab it back from the Public Pool. Doing so removes the game from the Public Pool so that other people can no longer clone it, but it does not affect the games people have already cloned.

Since everybody is seeing the same instructions you do, everybody in your group is able to clone and post games as you are.

III. Acquiring Games

There are three ways to acquire games to work on:

III.1 Request a game from the experimenter
Each period, the experimenter allots three games for you to work on. To request one of these games, you must click **New Game** (see Figure 1; Area B). **Each one of these games you complete will earn you 10 points.**

III.2 Clone a game from the Public Pool
You may clone a game from the Public Pool to work on. Each one of these games you complete will earn you the commission amount for that game. The commission is chosen by the person who posts the game (see Figure 3; Area B).

III.3 Clone or Retrieve a Private Game
At any time you may clone or retrieve games you have stored to your Private Games Collection (see Figure 4; Area C).

Please work on Quiz 2 on P. 10 now. Continue with the instructions when you are done.

IV. Structure of the Experiment

The experiment is divided into periods. At the beginning of each period, everything except **Total Earnings** will be reset. Note that your **Period Earnings** will be added to your **Total Earnings**. Any games in the Public Pool or your Private Games Collection will be discarded.

A period ends when everyone has solved all three of his allotted games (i.e. Group Requirement Achieved becomes “true”), or in 7 minutes, whichever occurs first. The experimenter will make an announcement to remind you the remaining time when there are 2 minutes left in the period.

In this experiment, there will be 10 periods and 1 trial period.

V. How to Use the Software

V.1 Your active game
Your “Active Game” is the game in the left panel that you are working on. To make a guess, you must select a color for each of the four slots by clicking the slot and choosing the color from the drop-down menu. Once you have selected four colors, click **Check** to submit your guess and see the hint for it (see Figure 2; Area A). Note that once you have clicked **Check** you cannot change your guess.

V.2 Work later
You may store your active game to your Private Games Collection at any time by clicking **Work Later** (see Figure 2; Area B). This sends your active game to your Private Games Collection. Your Private Games Collection is the list of games under the panel titled “Your Games” on the right side of the screen (see Figure 4; Area A).

V.3 Posting
To post your active game to the public pool, click **Post**. A window titled “Post Options” will appear (see Figure 5). Here you can set the commission for this game. To the right of the window is a preview of your game as it will appear in the public pool. To cancel posting, exit the window by clicking the “X” in the upper right corner. To post the game, click **Post** (see Figure 2; Area C).

V.4 Acquiring games
There are three ways to acquire a game:

1) *New game*
   You can request one of your three allotted games from the experimenter by clicking **New Game** (see Figure 1; Area B).

2) *Retrieving a private game*
   You can retrieve a game from your Private Games Collection by looking at the list of games under the panel titled “Your Games.” Here you can see the basic information of the game: Name, Guesses, and Time Added (see Figure 4; Area A).

   Name
   This is the name of the game (in number). Note that a clone will have the same name as its parent game but with an extra level number. For example, a clone of Game 1 will have the name 1.1, and a clone of Game 1.1 will have the name 1.1.1 (see Figure 4; Area B).

   Guesses
   This is the number of guesses already made in the game.

   Time Added
   This is the time you added the game into your Private Games Collection.

   Clicking on one of the games in the list will load a preview of the game on the right hand side of the screen. You may then choose **Clone** or **Retrieve** (see Figure 4; Area C). Cloning simply creates a copy of the game and leaves the original in your Private Games Collection, while retrieving it takes it out of your Private Games Collection.

3) *Retrieving a public game*
   You can browse games in the Public Pool list just as you can for those in the “Your Games” list. Here you also have all the basic information of the game. In addition to Name, Guesses, and Time Added, you also have Commission and Posted By (see Figure 3; Area A). Click on the column headers on the list to sort the games.

   Commission
   This is the number of points you earn by solving the cloned game.

Posted By
This is the User Name of the person who posts the game. No participants will know which User Name corresponds to which participant.

Click on a game to load a preview of the game on the right hand side of the screen. To clone and work on this game, click **Clone** (see Figure 3; Area B). If this game is yours, you will be able to **Grab** it out of the Public Pool. Grabbing removes the game from the Public Pool so other people will no longer be able to view and/or clone it. But this does not affect the games people already cloned.

Note: You can only acquire games when you do not have an active game. If you have an active game, you must complete it or store it to your Private Games Collection in order to work on a new game.

V.5 Information panel

You can keep track of various statistics by looking at the Information Panel on the bottom right-hand part of the screen (see Figure 1; Area C). Here is the available information:

User Name
Every person in this experiment is identified by a User Name (e.g. User 1, User 2, and so on). Your real name will be anonymous.

Potential Period Earnings
You will see an increase in your potential period earnings whenever you solve a game (or someone solves a game you post). The points you see here will be transferred to the field **Period Earnings** if **Group Requirement Achieved** becomes “True”.

Period Earnings
This will be zero until everyone has solved all three of his allotted games.

Total Earnings
This is the amount of <u>US$</u> you have accrued in **ALL** periods throughout the experiment. Your total earnings are simply the sum of your **Period Earnings** in dollars.

Games Left for You
This is the number of games left from the three the experimenter has allotted for you in the current period. If it reaches 0, you will not be able to request more games from the experimenter, but you will be allowed to work on public games.

Your Allotted Games Solved
This is the number of allotted games you have solved and/or the clones of your allotted games solved by others.

Group Requirement Achieved is “False” until everyone has solved three of his or her allotted games. It will become “True” when this requirement is fulfilled.

Time
This is the current time.

At the end of the experiment, the experimenter will come to each of you to record your total earnings. After that, we will shut down your screens so other students will not be able to see your earnings.

<u>This is the end of the instructions. Please work on Quiz 3 on P.11.</u>

Quiz 1

Please provide the hints (the black pegs and/or white pegs you expect to see) by writing B (black peg) or W (white peg) in the boxes provided.

The numbers (1-6) in the circles represent the six different colors (blue, red, green, yellow, cyan, pink) that you will see in the actual experiment. However, in the experiment, you will see both the colors and the numbers (if you click on **Display Color Numbers**).

Note: keep in mind that the position of the black and white pegs does not necessarily correspond to the positions of the guesses. Black pegs are always shown first (i.e. to the left of white pegs).

Please turn to the next page.

Example:

The hidden combination is

2 4 1 6

Your guess is:

4 5 1 2

Hint:

B W W

1. The hidden combination is

2 3 1 5

Your guess is:

5 3 1 2

Hint:

Quiz 2

Person 1 posts a game with the name, Game 2, which is worth 10 points and sets the commission to 5.

1. Person 2 clones this game. Therefore, the cloned game, Game 2.1 is created. How many points will Persons 1 and 2 each receive, if Person 2 solves Game 2.1?

   Person 1: ☐ points

   Person 2: ☐ points

2. After Person 2 has worked on Game 2.1, he however decides to repost it to the public pool and sets the commission to 3. Person 3 clones it, thereby creating Game 2.1.1. If Person 3 solves Game 2.1.1, how many points will Person 1, 2, and 3 each receive?

   Person 1: ☐ points

   Person 2: ☐ points

   Person 3: ☐ points

3. Now if Person 3 has not solved Game 2.1.1, and Person 2 is still working on Game 2.1 after he has posted it. This means that Person 2 and Person 3 are working concurrently on Game 2. If Person 2 solves Game 2.1 first, how many points will Persons 1, 2, and 3 each receive?

   Person 1: ☐ points

   Person 2: ☐ points

   Person 3: ☐ points

Quiz 3

1. Each person is allotted three games. You have solved two of your own games that are worth 10 points each, and your third game is solved by another person whom you have agreed to pay 4 points to. However, not every person in this experiment has solved all three of his games yet. What will you see in the following fields?

   Potential Period Earnings:

   Period Earnings:

   Games Left for You:

   Your Allotted Games Solved:

   Group Requirement Achieved:

2. Now every person has solved three games, what do you see in the following fields?

   Potential Period Earnings:

   Period Earnings:

   Games Left for You:

   Your Allotted Games Solved:

   Group Requirement Achieved:

<u>Please raise your hand when you are done so the experimenter can come to check your answers.</u>

Figure 1

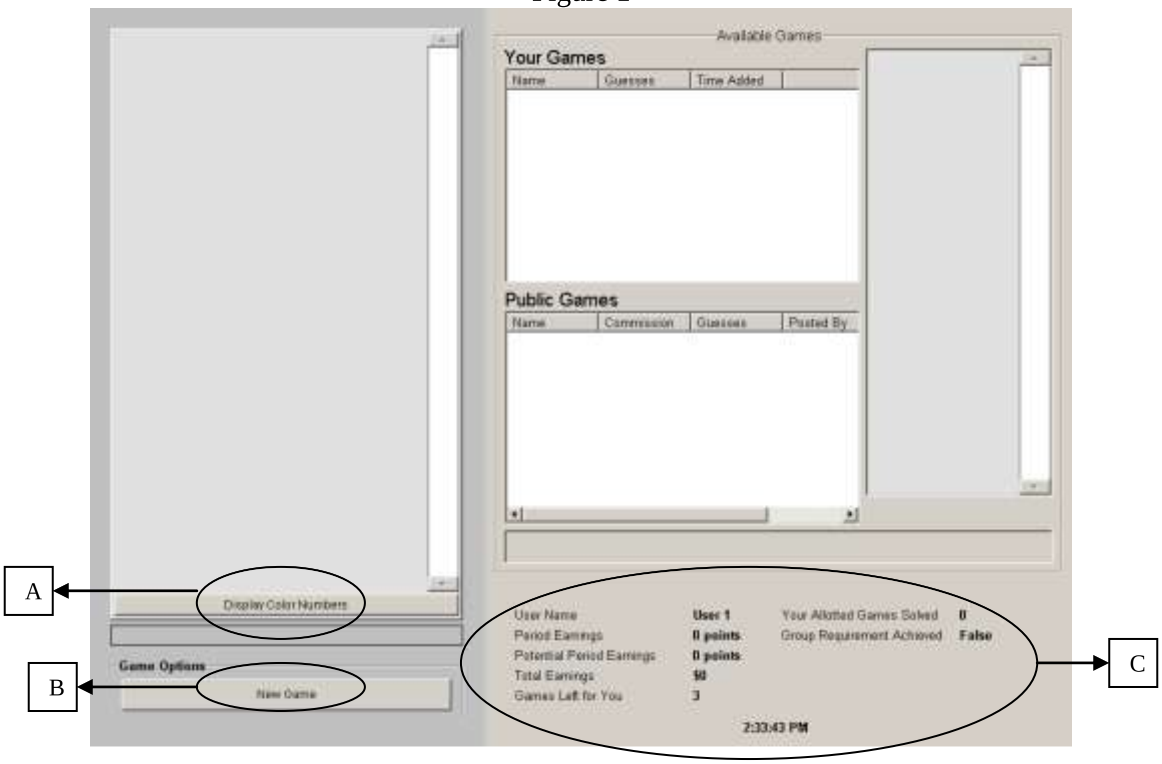


Figure 2

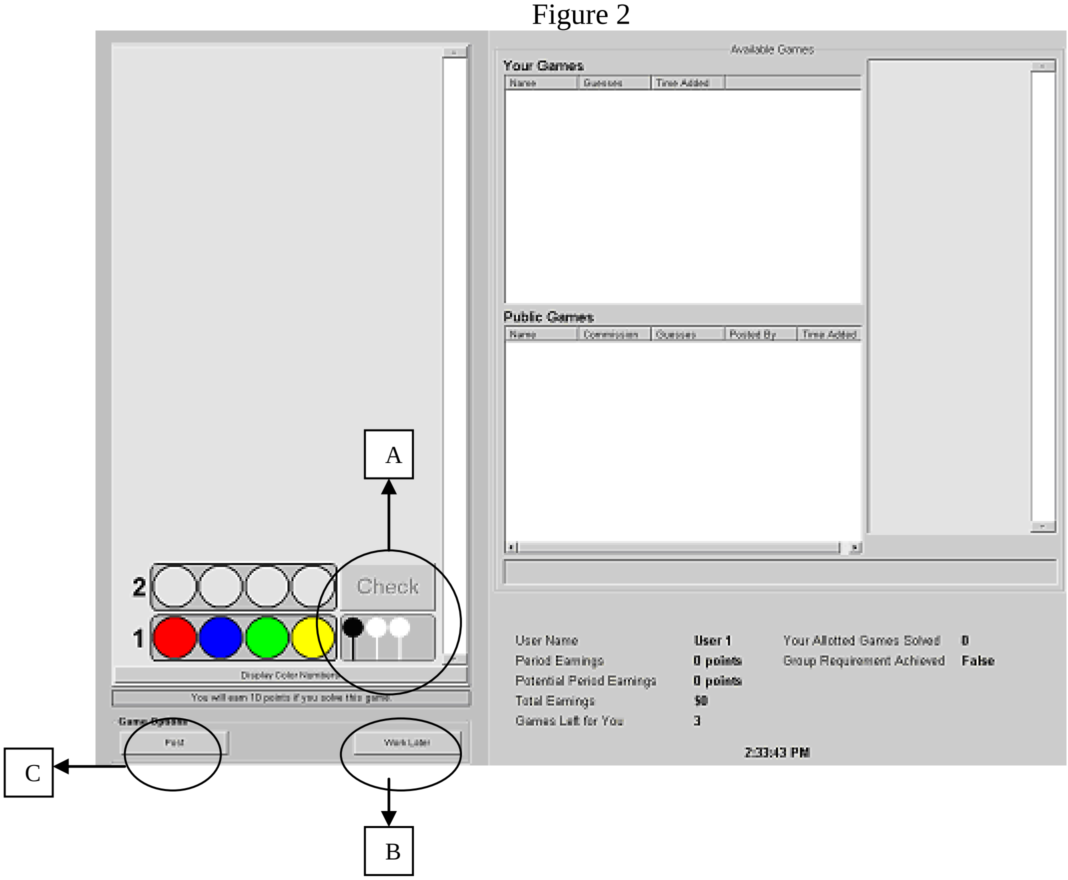


Figure 3

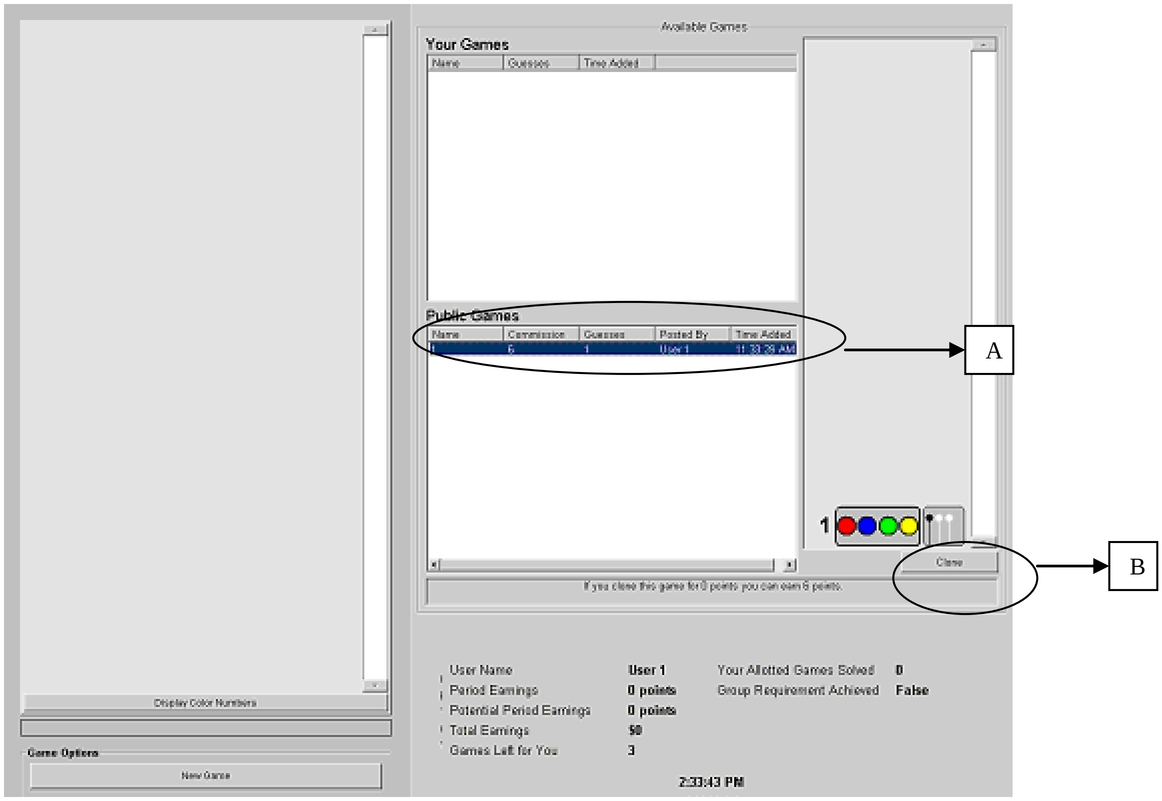

Available Games
Your Games
Public Games
A
B
Clone
User Name
User 1
Period Earnings
0 points
Potential Period Earnings
0 points
Total Earnings
50
Games Left for You
3
Your Allotted Games Solved
0
Group Requirement Achieved
False
2:33:43 PM
Game Options
New Game

Figure 4

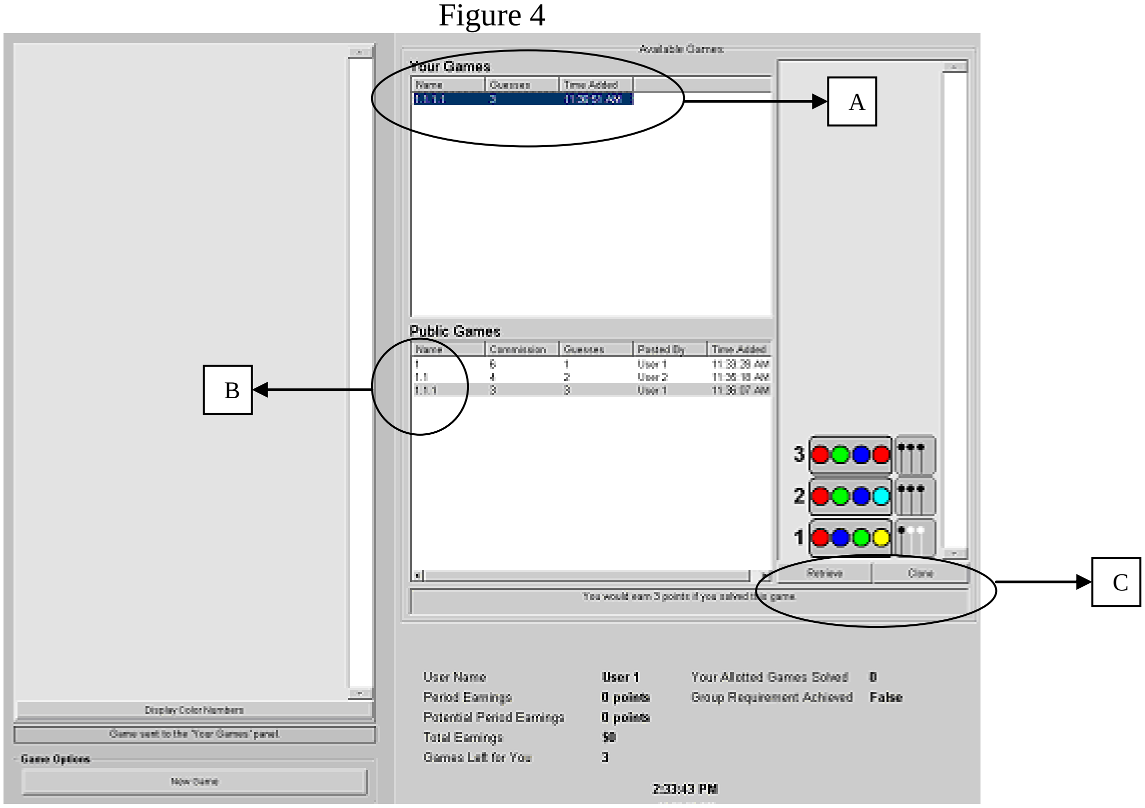
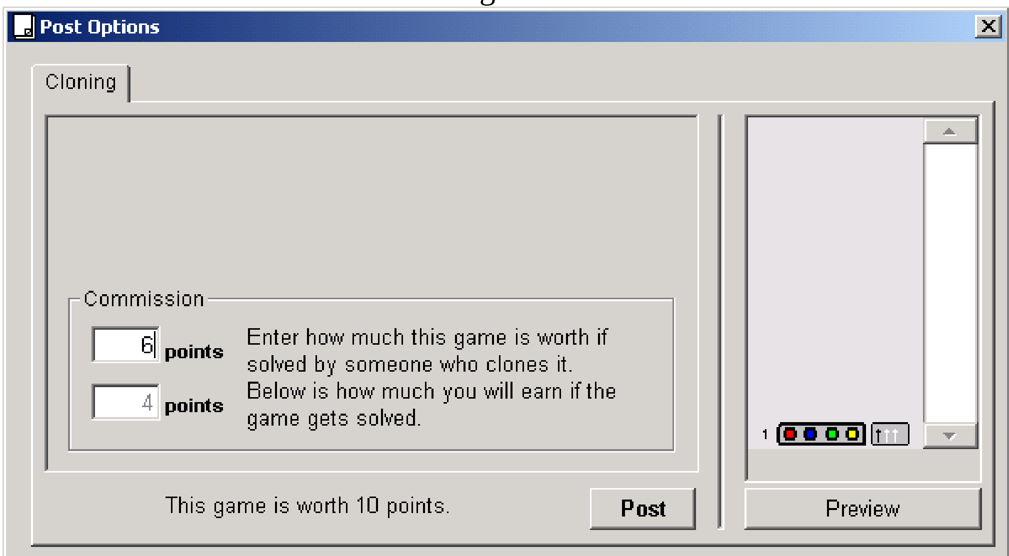

Available Games
Your Games
Public Games
A
B
C
Retrieve
Clone
User Name
User 1
Period Earnings
0 points
Potential Period Earnings
0 points
Total Earnings
50
Games Left for You
3
Your Allotted Games Solved
0
Group Requirement Achieved
False
2:33:43 PM
Game Options
New Game

Figure 5



Post Options
Cloning
Commission
6 points
Enter how much this game is worth if solved by someone who clones it.
4 points
Below is how much you will earn if the game gets solved.
1
This game is worth 10 points.
Post
Preview

APPENDIX C

Proof of Sender's Best Responses

The sender's profit function is

$$\pi_s(N_s^o, N_s^c, t_s^c) = p_s^o N_s^o + \frac{p_s^c N_s^c}{t_s^c f^c} - C_s(N_s^o, N_s^c, t_s^c) \tag{C.1}$$

The Lagrangian is:

$$\mathcal{L} = \pi(\cdot) - \lambda_1^c(t_s^c - 1) + \lambda_2^c(t_s^c - \frac{1}{f^c}) + \mu^o N_s^o + \mu^c N_s^c, \tag{C.2}$$

where $\lambda_1^c, \lambda_2^c, \mu^c, \mu^o \geq 0$.

The complementary slackness conditions are:

$$\lambda_1^c(t_s^c - 1) = 0 \tag{C.3}$$

$$\lambda_2^c(t_s^c - \frac{1}{f^c}) = 0 \tag{C.4}$$

$$\mu^o N_s^o = 0 \tag{C.5}$$

$$\mu^c N_s^c = 0 \tag{C.6}$$

FOCs:

$$p_s^o = \frac{\partial C_s}{\partial N_s^o} - \mu^o \tag{C.7}$$

$$\frac{p_s^c}{t_s^c f^c} = \frac{\partial C_s}{\partial N_s^c} - \mu^c \tag{C.8}$$

$$\frac{-p_s^c N_s^c}{(t_s^c)^2 f^c} - \lambda_1^c + \lambda_2^c = \frac{\partial C_s}{\partial t_s^c} \tag{C.9}$$

Case 1: $N_s^o, N_s^c > 0 \implies \mu^o = \mu^c = 0$.

(C.7) implies $p_s^o = \frac{\partial C_s}{\partial N_s^o}$. (C.8) implies $\frac{p_s^c}{t_s^c f^c} = \frac{\partial C_s}{\partial N_s^c}$.

Subcase 1: $t_s^c = 1 \implies \lambda_2^c = 0$

Combining (C.8) and (C.9), we have $-N_s^c \frac{\partial C_s}{\partial N_s^c} - \lambda_1^c = \frac{\partial C_s}{\partial t_s^c}$. This implies $-N_s^c \frac{\partial C_s}{\partial N_s^c} \geq \frac{\partial C_s}{\partial t_s^c}$.

Subcase 2: $t_s^c = \frac{1}{f^c} \implies \lambda_1^c = 0$

Combining (C.8) and (C.9), we have $-N_s^c \frac{\partial C_s}{\partial N_s^c} + \lambda_2^c = \frac{\partial C_s}{\partial t_s^c}$. This implies $-N_s^c \frac{\partial C_s}{\partial N_s^c} \leq \frac{\partial C_s}{\partial t_s^c}$.

Subcase 3: $t_s^c \in (\frac{1}{f^c}, 1) \implies \lambda_1^c = \lambda_2^c = 0$.

(C.9) implies $N_s^c \frac{\partial C_s}{\partial N_s^c} = -t_s^c \frac{\partial C_s}{\partial t_s^c}$.

Case 2: $N_s^o > 0, N_s^c = 0 \implies \mu^o = 0$.

(C.7) implies $p_s^o = \frac{\partial C_s}{\partial N_s^o}$. (C.8) implies $\frac{\partial C_s}{\partial N_s^c} \geq \frac{p_s^c}{t_s^c f^c}$.

Subcase 1: $t_s^c = 1 \implies \lambda_2^c = 0$

(C.9) implies $-\lambda_1^c = \frac{\partial C_s}{\partial t_s^c}$. (C.8) implies $\frac{\partial C_s}{\partial N_s^c} \geq \frac{p_s^c}{f^c}$.

Subcase 2: $t_s^c = \frac{1}{f^c} \implies \lambda_1^c = 0$

(C.9) implies $\lambda_2^c = \frac{\partial C_s}{\partial t_s^c}$, which contradicts $\frac{\partial C_s}{\partial t_s^c} < 0$.

Subcase 3: $t_s^c \in (\frac{1}{f^c}, 1) \implies \lambda_1^c = \lambda_2^c = 0$.

(C.9) implies $\frac{\partial C_s}{\partial t_s^c} = 0$, which is a contradiction because $\frac{\partial C_s}{\partial t_s^c} < 0$.

Case 3: $N_s^o = 0, N_s^c > 0 \implies \mu^c = 0$.

(C.7) implies $\frac{\partial C_s}{\partial N_s^o} \geq p_s^o$. (C.8) implies $\frac{p_s^c}{t_s^c f^c} = \frac{\partial C_s}{\partial N_s^c}$.

The subcase results of t_s^c are the same as Case 1's.

Case 4: $N_s^o = N_s^c = 0$.

<u>Subcase 1:</u> $t_s^c = 1 \implies \lambda_2^c = 0$

(C.9) implies $-\frac{\partial C_s}{\partial t_s^c} \geq 0$. (C.7) implies $\frac{\partial C_s}{\partial N_s^o} \geq p_s^o$. (C.8) implies $\frac{\partial C_s}{\partial N_s^c} \geq \frac{p_s^c}{f^c}$.

<u>Subcase 2:</u> $t_s^c = \frac{1}{f^c} \implies \lambda_1^c = 0$

(C.9) implies $\lambda_2^c = \frac{\partial C_s}{\partial t_s^c}$, which contradicts $\frac{\partial C_s}{\partial t_s^c} < 0$.

<u>Subcase 3:</u> $t_s^c \in (\frac{1}{f^c}, 1) \implies \lambda_1^c = \lambda_2^c = 0$

(C.9) implies $\frac{\partial C_s}{\partial t_s^c} = 0$, which contradicts $\frac{\partial C_s}{\partial t_s^c} < 0$.

Lastly, note that $\frac{-\frac{\partial C_s}{\partial N_s^c}}{\frac{\partial C_s}{\partial t_s^c}} \frac{N_s^c}{t_s^c} = \frac{-\frac{\partial \ln C_s}{\partial \ln N_s^c} \frac{C_s}{N_s^c}}{\frac{\partial \ln C_s}{\partial \ln t_s^c} \frac{C_s}{t_s^c}} \frac{N_s^c}{t_s^c} = \frac{-\frac{\partial \ln C_s}{\partial \ln N_s^c}}{\frac{\partial \ln C_s}{\partial \ln t_s^c}} \equiv \frac{-E_{C_s, N_s^c}}{E_{C_s, t_s^c}}$.

Q.E.D.

APPENDIX D

Proof of Advertiser's Best Responses

The Lagrangian is:

$$\mathcal{L} = \sum_j (p_a^j \theta^j - p_s^j) n_a^j - C_a(\sum_j \theta^j n_a^j) + \mu^o n_a^o + \mu^c n_a^c, \tag{D.1}$$

where $\mu^c, \mu^o \geq 0$.

The complementary slackness conditions are:

$$\mu^o n_a^o = 0 \tag{D.2}$$

$$\mu^c n_a^c = 0 \tag{D.3}$$

FOCs:

$$\forall j : p_a^j \theta^j = p_s^j + \theta^j C_a'(\sum_j \theta^j n_a^j) - \mu^j \tag{D.4}$$

$$p_a^c \theta^c = p_s^c + \theta^c C_a'(\sum_j \theta^j n_a^j) - \mu^c \tag{D.5}$$

and

$$p_a^o \theta^o = p_s^o + \theta^o C_a'(\sum_j \theta^j n_a^j) - \mu^o \tag{D.6}$$

Case 1: $n_a^o > 0, n_a^c > 0$.

$n_a^c > 0 \implies \mu^c = 0$. (D.5) implies $\theta^c C_a'(\sum_j \theta^j n_a^j) + p_s^c = \theta^c p_a^c$.

$n_a^o > 0 \implies \mu^o = 0$. (D.6) implies $\theta^o C_a'(\sum_j \theta^j n_a^j) + p_s^o = \theta^o p_a^o$.

Case 2: $n_a^o = 0, n_a^c > 0$.

$n_a^c > 0 \implies \mu^c = 0$. (D.5) implies $\theta^c C_a'(\sum_j \theta^j n_a^j) + p_s^c = \theta^c p_a^c$.

(D.6) implies $\theta^o C_a'(\sum_j \theta^j n_a^j) + p_s^o \geq \theta^o p_a^o$.

Case 3: $n_a^o = 0, n_a^c = 0$.

(D.5) implies $\theta^c C_a'(\sum_j \theta^j n_a^j) + p_s^c \geq \theta^c p_a^c$.

(D.6) implies $\theta^o C_a'(\sum_j \theta^j n_a^j) + p_s^o \geq \theta^o p_a^o$.

Case 4: $n_a^o > 0, n_a^c = 0$.

$n_a^o > 0 \implies \mu^o = 0$. (D.6) implies $\theta^o C_a'(\sum_j \theta^j n_a^j) + p_s^o = \theta^o p_a^o$.

(D.5) implies $\theta^c C_a'(\sum_j \theta^j n_a^j) + p_s^c \geq \theta^c p_a^c$.

Q.E.D.

APPENDIX E

Proof of Recipients' Best Responses

For low-type recipients, $v^g_{\underline{r}}$ and $v^{II}_{\underline{r}}$ are zero anyway, but $\kappa^o_{\underline{r}} = 1$ implies that $v^I_{\underline{r}}$ only strictly increases (remains unchanged) if $N^o_r > (=)0$. Thus, the best responses for low-type recipients are $\kappa^o_{\underline{r}} = 0$ if $N^o_r > 0$ and $\kappa^o_{\underline{r}} = 0$ and 1 if $N^o_r = 0$. For high-type recipients, there is no effect on Type II errors (equation (4.4)) because for the open channel $t^j = f^j = 1$, so the term for $j = o$ is zero. However, $\kappa^o_{\bar{r}} = 1$ implies that $v^g_{\bar{r}}$ weakly increases for high-type recipients because of the max operator in (equation (4.2)). For high-type recipients, the question then is whether the utility increase with the increase in $v^g_{\bar{r}}$ would at least offset the utility decrease with the increase in $v^I_{\bar{r}}$. When $N^o_r = 0$, the best responses are $\kappa^o_{\bar{r}} = 0$ and 1 because both the changes in $v^g_{\bar{r}}$ and $v^I_{\bar{r}}$ are zero. When $N^o_r > 0$ and $N^c_r = 0$, the best response is $\kappa^o_{\bar{r}} = 1$ because the utility increase in $v^g_{\bar{r}}$ exceeds the utility decrease in $v^I_{\bar{r}}$. We must have $U_{\bar{r}}(\kappa^o_{\bar{r}} = 1) - U_{\bar{r}}(\kappa^o_{\bar{r}} = 0) > 0$. When $N^o_r > 0$ and $N^c_r > 0$, the best responses are $\kappa^o_{\bar{r}} = 0$ or 1 or both, depending on the magnitude of changes in $v^g_{\bar{r}}$ and $v^I_{\bar{r}}$. In this case, $\kappa^o_{\bar{r}} = 1$ can be a best response only if $p^c_a > p^o_a$, else both $v^g_{\bar{r}}$ at best unchanged but $v^I_{\bar{r}}$ increases. Q.E.D.

APPENDIX F

Proof of Nash Equilibrium

Recall that $\hat{N}_s^o = \hat{n}_a^o = \hat{n}_{\bar{r}}^o + \hat{n}_{\underline{r}}^o$ and $\frac{\hat{N}_s^c}{\hat{t}_s^c f^c} = \hat{n}_a^c = \hat{n}_{\bar{r}}^c + \hat{n}_{\underline{r}}^c$. Assumption IV.2 implies $\hat{\kappa}_{\bar{r}}^c = \hat{\kappa}_{\underline{r}}^c = 1$. There are four cases.

Case a: $\hat{n}_a^o = \hat{n}_a^c = 0$.

$n_a^o = n_a^c = 0$ implies that $v_r^g = 0$ by (equation (4.22)). $v_r^g = 0 \Longrightarrow p_a^o, p_a^c = \infty$ because $v_r^g = \max_j\{\frac{\kappa_r^j w_r}{p_a^j}\}$(equation (4.2)). $p_a^o, p_a^c = \infty$ implies that the advertiser's maximization problem is not well defined, contradicting $n_a^o = n_a^c = 0$ being the solution.

Case b: $\hat{n}_a^o = 0, \hat{n}_a^c > 0$.

Note that $\pi_a(0, n_a^c) = (p_a^c\theta^c - p_s^c - c_a\theta^c)n_a^c = w_r - p_s^c n_a^c - c_a\frac{w_r}{p_a^c}$(since $\frac{w_r}{p_a^c} = \theta^c n_a^c$), and $\pi_a(n_a^o, 0) = (p_a^o\theta^o - p_s^o - c_a\theta^o)n_a^o = w_r - p_s^o n_a^o - c_a\frac{w_r}{p_a^o}$(since $\frac{w_r}{p_a^o} = \theta^o n_a^o$).$\hat{n}_a^o = 0$ and $\hat{n}_a^c > 0$ as a profit maximizer implies that $\pi_a(0, \hat{n}_a^c) - \pi_a(n_a^o, 0) = p_s^o n_a^o - \hat{p}_s^c\hat{n}_a^c + c_a\frac{w_r}{p_a^o} - c_a\frac{w_r}{\hat{p}_a^c} \geq 0$ for all n_a^o.

(i) When $\kappa_{\bar{r}}^o = \kappa_{\bar{r}}^c = 1$, we need $p_s^o n_a^o - \hat{p}_s^c\hat{n}_a^c \geq 0$ because $c_a\frac{w_r}{p_a^o} - c_a\frac{w_r}{\hat{p}_a^c} \leq 0$. (The last inequality is implied by $\hat{p}_a^c \leq p_a^o$, which is true because $n_a^c > 0$. Suppose otherwise that $\hat{p}_a^c > p_a^o, \kappa_{\bar{r}}^o = \kappa_{\bar{r}}^c = 1$ implies $v_r^{g,c} = 0$ and $\theta^c = 0$, violating the condition to ensure $\hat{n}_a^c > 0$ by Result IV.4.) But $p_s^o n_a^o - \hat{p}_s^c \hat{n}_a^c \geq 0$ can't be satisfied unless $n_a^o > \hat{n}_a^c$ because $\hat{p}_s^c > p_s^o$ (implied by Result IV.3 and the zero profit condition that makes the weak inequalities in the best response strict). But $n_a^o > \hat{n}_a^c$ contradicts with $\hat{n}_a^o = 0$ and $\hat{n}_a^c > 0$.

(ii) When $\kappa_{\bar{r}}^o = 0$,we have $\theta^o = 0$. This implies that $n_a^o = 0$ by Result IV.4. We now check if $n_a^c = 0$ or $n_a^c > 0$ constitutes part of the equilibrium, if any. If $n_a^o = n_a^c = 0$, it can't be an equilibrium as explained in Case a. Else if $n_a^o = 0$ and $n_a^c > 0$, both recipient types could choose to opt-in or not as a best responses by Result IV.5. When $\kappa_{\bar{r}}^o = 1$, we are back to (i), which we eliminated. $\kappa_{\bar{r}}^o = 0$ then is the uneliminated best response for the high types. For the low types, $\kappa_{\underline{r}}^o = 1$ and 0 are still the uneliminated best responses. To ensure $\hat{n}_a^c > 0$ and $\hat{n}_a^o = 0$, we need $\hat{\theta}^c \hat{p}_a^c = \hat{\theta}^c c_a + \hat{p}_s^c = \hat{\theta}^c c_a + c_s^c \hat{t}_s^c f^c$ and $\hat{\theta}^o \hat{p}_a^o < \hat{\theta}^o c_a + \hat{p}_s^o < \hat{\theta}^o c_a + c_s^o$ by Results IV.3 and IV.4, and the zero profit conditions. We call this group of equilibria the status quo Nash equilibria because $\kappa_{\bar{r}}^o = \kappa_{\underline{r}}^o = 0$ is the same as in the status quo in terms of decision made, and $\kappa_{\bar{r}}^o = 0$ and $\kappa_{\underline{r}}^o = 1$ is the same as in the status quo in terms of the *utilities* and *profit* realized.

<u>Case c: $\hat{n}_a^o > 0, \hat{n}_a^c = 0$.</u>

Result IV.5 implies that if $n_a^o > 0$ and $n_a^c = 0, \kappa_{\bar{r}}^o = 1$ and $\kappa_{\underline{r}}^o = 0$ is the best response. What is left is to show that if $\kappa_{\bar{r}}^o = 1$ and $\kappa_{\underline{r}}^o = 0, n_a^o > 0$ and $n_a^c = 0$ is the best response. Since $t_s^c \leq t_s^o = 1$ and $\kappa_{\bar{r}}^o = \kappa_{\bar{r}}^c = 1$, we have $\theta^o \geq \theta^c$. When $n_a^o > 0$, setting $n_a^c > 0$ weakly increases profit only if $p_a^o = p_a^c$ to justify why recipients buy from both channels $(v_r^{g,o}, v_r^{g,c} > 0)$ (from equation (4.2)). But $p_a^o = p_a^c$ implies that $v_{\bar{r}}^g$ is the same whether $n_a^c > 0$. But for each fraction of $v_{\bar{r}}^g$ satisfied by the sales in the censored channel instead of the open channel, the decrease in n_a^o has to be compensated by an even greater increase in n_a^c. With no increase in sales but the need, by $\theta^o \geq \theta$, to increase mail volume using the more costly censored channel, the profit is not maximized. The only best response left is $n_a^o = 0$, which is already eliminated in Case a.

To ensure $\hat{n}_a^c = 0$ and $\hat{n}_a^o > 0$, we need $\hat{\theta}^c \hat{p}_a^c < \hat{\theta}^c c_a + \hat{p}_s^c < \hat{\theta}^c c_a + c_s^c \hat{t}_s^c f^c$ and $\hat{\theta}^o \hat{p}_a^o = \hat{\theta}^o c_a + \hat{p}_s^o = \hat{\theta}^o c_a + c_s^o$ by Results IV.3 and IV.4, and the zero profit conditions.

Case d: $\hat{n}_a^o > 0, \hat{n}_a^c > 0.$

We already showed in Case c that when $\kappa_{\bar{r}}^o = 1, n_a^c, n_a^o > 0$ is not a best response. When $\kappa_{\bar{r}}^o = 0$,we already showed in Case b (ii) that $n_a^o > 0$ is not a best response. Thus, $n_a^c, n_a^o > 0$ is not an equilibrium.

Q.E.D.

APPENDIX G

Proof of Mail Volume Changes

(i) For high-type recipients:

$$\frac{\hat{N}^{o}_{\bar{r}}}{\hat{t}^{o} f^{o}} \leq \frac{\hat{N}^{c,\infty}_{\bar{r}}}{\hat{t}^{c,\infty} f^{c}} \iff \hat{n}^{o}_{a} \leq \frac{R_{\bar{r}}}{R} \hat{n}^{c,\infty}_{a} \iff \tag{G.1}$$

$$\frac{\hat{v}^{g,o}_{\bar{r}}}{\hat{\theta}^{o}} \leq \frac{R_{\bar{r}}}{R} \frac{\hat{v}^{g,c,\infty}_{\bar{r}}}{\hat{\theta}^{c,\infty}} \iff \frac{w_{\bar{r}}}{\hat{\theta}^{o} \hat{p}^{o}_{a}} \leq \frac{R_{\bar{r}}}{R} \frac{w_{\bar{r}}}{\hat{\theta}^{c,\infty} \hat{p}^{c,\infty}_{a}} \tag{G.2}$$

Since the advertiser's problem gives $\hat{p}^{o}_{a} \hat{\theta}^{o} = \hat{\theta}^{o} c_{a} + \hat{p}^{o}_{s}$ and $\hat{\theta}^{c,\infty} \hat{p}^{c,\infty}_{a} = \hat{\theta}^{c,\infty} c_{a} + \hat{p}^{c,\infty}_{s}$, and the sender's problem gives $\hat{p}^{o}_{s} = c^{o}_{s}$ and $\hat{p}^{c,\infty}_{s} = c^{c}_{s} \hat{t}^{c,\infty} f^{c}$, the last inequality becomes:

$$\hat{\theta}^{o} c_{a} + c^{o}_{s} \geq \frac{R}{R_{\bar{r}}} (\hat{\theta}^{c,\infty} c_{a} + c^{c}_{s} \hat{t}^{c,\infty} f^{c}) \iff \hat{\theta}^{o} \tag{G.3}$$

For low-type recipients, they receive less mail because they don't use the open channel and the mail sent to the censored channel is zero.

(ii) For the total volume received by all recipients:

$$\sum_j \frac{\hat{N}^j_{\bar{r}} + \hat{N}^j_{\underline{r}}}{\hat{t}^j f^j} \leq \frac{\hat{N}^{c,\infty}_{\bar{r}} + \hat{N}^{c,\infty}_{\underline{r}}}{\hat{t}^{c,\infty} f^c} \iff \tag{G.4}$$

$$\hat{n}^o_a \leq \hat{n}^{c,\infty}_{\bar{r}} + \hat{n}^{c,\infty}_{\underline{r}} (\because \hat{N}^o_{\underline{r}} = \hat{N}^c_r = 0) \iff \tag{G.5}$$

$$\frac{\hat{v}^{g,o}_{\bar{r}}}{\hat{\theta}^o} \leq \frac{\hat{v}^{g,c,\infty}_{\bar{r}}}{\hat{\theta}^{c,\infty}} \iff \frac{w_{\bar{r}}}{\hat{\theta}^o \hat{p}^o_a} \leq \frac{w_{\bar{r}}}{\hat{\theta}^{c,\infty} \hat{p}^{c,\infty}_a} \iff \tag{G.6}$$

$$\hat{\theta}^o c_a + c^o_s \geq \hat{\theta}^{c,\infty} c_a + c^c_s \hat{t}^{c,\infty} f^c \iff \hat{\theta}^o \geq \hat{\theta}^{c,\infty} + \frac{c^c_s \hat{t}^{c,\infty} f^c - c^o_s}{c_a} \tag{G.7}$$

Q.E.D.

APPENDIX H

Proof of Welfare Changes

$$\lim_{f^o \to \infty} U_r(\hat{v}_r^g, \hat{v}_r^I, \hat{v}_r^{II}) = U_r(\lim_{f^o \to \infty} \hat{v}_r^g, \lim_{f^o \to \infty} \hat{v}_r^I, \lim_{f^o \to \infty} \hat{v}_r^{II}) \tag{H.1}$$

Since $\hat{U}_r - \lim_{f^o \to \infty} \hat{U}_r \geq 0$ if (a) $\hat{v}_r^g \geq \lim_{f^o \to \infty} \hat{v}_r^g$(with $\hat{v}_{\bar{r}}^g > \lim_{f^o \to \infty} \hat{v}_{\bar{r}}^g$),(b) $\hat{v}_r^I \leq \lim_{f^o \to \infty} \hat{v}_r^I$(with $\hat{v}_{\underline{r}}^I < \lim_{f^o \to \infty} \hat{v}_{\underline{r}}^I$), and (c) $\hat{v}_r^{II} \leq \lim_{f^o \to \infty} \hat{v}_r^{II}$, we prove each of these inequalities below.

(i) Inequality (a) is $\hat{v}_r^g \geq \lim_{f^o \to \infty} \hat{v}_r^g$, or:

$$\max_j \{ \frac{\kappa_r^j w_r}{p_a^j} \} \geq \frac{\hat{\kappa}_r^{c,\infty} w_r}{\hat{p}_a^{c,\infty}} \tag{H.2}$$

It holds for $w_{\underline{r}} = 0$ because both sides are zero. For $w_{\bar{r}} = 1, \hat{\kappa}_{\bar{r}}^o = 1$ by Result IV.5 and $\kappa_{\bar{r}}^c = \hat{\kappa}_{\bar{r}}^{c,\infty} = 1$ by Assumption IV.2. (H.2) becomes:

$$\max_j \{ \frac{1}{p_a^j} \} \geq \frac{1}{\hat{p}_a^{c,\infty}}, \tag{H.3}$$

which holds with strict inequality since $\hat{p}_a^o < \hat{p}_a^{c,\infty}$. This is because $\hat{p}_a^{c,\infty} = c_a + \frac{\hat{p}_s^{c,\infty}}{\hat{\theta}^{c,\infty}}$

and $\hat{p}_a^o = c_a + \frac{\hat{p}_s^o}{\hat{\theta}^o}$, and $\hat{\theta}^o > \hat{\theta}^{c,\infty}$ ($\frac{R_{\bar{r}}^o}{R^o} = 1$ by Proposition IV.6) and $\hat{p}_s^o < \hat{p}_s^{c,\infty}$(where $\hat{p}_s^{c,\infty} = \hat{t}_s^{c,\infty} f^c c_s^{c,\infty}, \hat{p}_s^o = c_s^o,\ \hat{t}_s^{c,\infty} f^c \geq 1$ and $c_s^{c,\infty} > c_s^o$).

(ii) Inequality (b) is $\hat{v}_r^I \leq \lim_{f^o \to \infty} \hat{v}_r^I$, or:

$$\sum_{j\in\{o,c\}} (1 - w_r + w_r\epsilon)\hat{\kappa}_r^j \frac{\hat{N}_r^j}{\hat{t}^j f^j} \leq (1 - w_r + w_r\epsilon)\hat{\kappa}_r^{c,\infty} \frac{\hat{N}_r^{c,\infty}}{\hat{t}^{c,\infty} f^c} \tag{H.4}$$

For $w_{\underline{r}} = 0$, since $\hat{\kappa}_{\underline{r}}^o = 0$ by Result IV.5, $\kappa_r^c = \hat{\kappa}_r^{c,\infty} = 1$ by Assumption IV.2, (H.4) becomes:

$$\frac{\hat{N}_{\underline{r}}^c}{\hat{t}^c f^c} \leq \frac{\hat{N}_{\underline{r}}^{c,\infty}}{\hat{t}^{c,\infty} f^c},$$

which is true because $\hat{N}_r^c = 0$ by Proposition IV.6. If $\hat{N}_{\underline{r}}^{c,\infty} > 0$, the inequality will hold with a strict sign.

For $w_{\bar{r}} = 1, \hat{N}_r^c = 0$ and $\kappa_r^c = \hat{\kappa}_r^{c,\infty} = 1$ implies that (H.4) becomes (note that if $\epsilon = 0$, (H.4) will be satisfied because both sides equal zero):

$$\frac{\hat{N}_{\bar{r}}^o}{\hat{t}^o f^o} \leq \frac{\hat{N}_{\bar{r}}^{c,\infty}}{\hat{t}^{c,\infty} f^c} \tag{H.5}$$

But we already proved in Proposition IV.7 the necessary and sufficient condition for $\frac{\hat{N}_{\bar{r}}^o}{\hat{t}^o f^o} \leq \frac{\hat{N}_{\bar{r}}^{c,\infty}}{\hat{t}^{c,\infty} f^c}$ to hold.

(iii) Inequality (c) is $\hat{v}_r^{II} \leq \lim_{f^o \to \infty} \hat{v}_r^{II}$, or:

$$\sum_{j\in\{o,c\}} (1-\epsilon) w_r \hat{\kappa}_r^j \hat{N}_r^j (1 - \frac{1}{\hat{t}^j f^j}) \leq (1-\epsilon) w_r \hat{\kappa}_r^{c,\infty} \hat{N}_r^{c,\infty} (1 - \frac{1}{\hat{t}^{c,\infty} f^c}) \tag{H.6}$$

It holds for $w_{\underline{r}} = 0$ because both sides are zero when $\epsilon = 0$. For $w_{\bar{r}} = 1$, since $\hat{\kappa}_{\bar{r}}^o = 1$ by Result IV.5, $\kappa_r^c = \hat{\kappa}_r^{c,\infty} = 1$ by Assumption IV.2, (H.6) becomes:

$$\sum_{j\in\{o,c\}} \hat{N}_r^j (1 - \frac{1}{\hat{t}^j f^j}) \leq \hat{N}_r^{c,\infty} (1 - \frac{1}{\hat{t}^{c,\infty} f^c}), \tag{H.7}$$

which is true because $\hat{N}_r^c = 0$ by Proposition IV.6 and $\hat{t}^o f^o = 1$.

Q.E.D.

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