The Impact of Intelligent Agents on Electronic Markets: Customization, Preference Revelation and Pricing.

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Abstract

Apart from reducing buyer search costs, web-based commerce has also enabled the use of intelligent agent technologies that reduce seller search costs by targeting buyers, customizing, and pricing products in real-time. Our model of an electronic market with customizable products analyzes the pricing, profitability and welfare implications of these agent-based technologies that price dynamically, based on product preference and demographic information revealed by consumers. We find that in making the trade-off between better prices and better customization, consumers invariably choose less-than-ideal products. Furthermore, this trade-off impacts buyers on the higher end of the market more, and causes a transfer of consumer surplus towards buyers with a lower willingness to pay. As buyers adjust their product choices in response to better demand agent technologies, sellers may experience reduced revenues, since the gains from better buyer information are countered by the lowering of the total value created from the transactions. We study the strategic and welfare implications of these findings, and discuss managerial and technology development guidelines.

1 Introduction and motivation

It has been observed by several researchers that electronic markets have the potential to transform retail commerce, by reducing buyer transaction costs (Bakos, 1991, Malone, Yates and Benjamin, 1991). A number of papers have been written about the general problem of search that buyers encounter when they attempt to locate sellers, and the resulting store location and product differentiation choices that sellers make[1]. The approaches of these papers have also been adapted to settings involving electronic markets, most notably in Bakos (1997).

While the lowering of buyers' search costs is a crucial determinant of profits and welfare from electronic commerce, electronic markets are also causing another, equally profound change in commerce, by enabling and lowering the costs of a complementary form of search. Sellers in electronic markets now have an unprecedented ability to accurately search for, target and customize for their individual buyers. A recent article about Web-based commerce in The Economist explains that this

[1] See, for instance, Stigler, 1962, Diamond, 1971, and Salop, 1979.

"....is a move away from mass marketing, which starts with a product and finds customers to buy it, towards an information-led, one-to-one marketing, which may ultimately sell each individual a customized product."

Certainly, targeted selling existed well before commerce on the Web became popular. Sellers have sought to market directly to individual consumers for many years — in North America alone, this industry was worth $163 billion in 1998, and was responsible for three-fifths of the country's total spending on advertising. However, traditional direct marketing is imprecise, with typical success rates for mail-shot campaigns in mature markets being no better than 2%. The low conversion rates are largely because direct marketers have been forced to rely on imprecise consumer preference profiles, built using a combination of census data, questionnaires, electoral-roll information and credit-card data. Such information lacks the granularity and reliability required for precise and economically viable targeting.

Commerce on the Web mitigates this inadequacy in consumer information. Recent developments in Internet-related technologies have made it feasible for sellers to obtain near-perfect information on individual customers, and to provide products and services tailored precisely to the consumer's individual preferences, thus making the transition from product-led marketing to consumer-led marketing a reality. Foremost amongst them is the deployment and use of *intelligent agents (*for a description of some of these agents, see Maes, 1994). The existence of these agents radically transforms the dynamics of the buyer-seller transaction, as it creates, in some sense, an exclusive market for each buyer-seller pair. It also makes mass customization on a per-customer basis feasible. It opens up the possibility of perfect, first-degree price discrimination. Furthermore, it enables merchants to make intelligent associations across buyers.

While similar agents are also used to facilitate buyer search, we study the class of intelligent agents known as *demand agents.* These agents estimate buyer preferences, valuations and product tastes, by combining consumer purchase histories with individual and site demographics. They use this information to price and recommend products to these customers. They also provide buyers with product information, and could help sellers design new products and marketing strategies. Many agents use collaborative filtering – a technique that uses mathematical algorithms to factor preferences and compare an individual's preferences with the preferences of other users — to make recommendations based on these comparisons (see, for instance, Balabanovic and Shoham 1997, Kautz, Selman and Shah 1997, Stohr and Viswanathan, 1999). Net Perceptions, for instance, sells a demand agent with consumer profiling capabilities that remembers the preferences of shoppers based on their past purchases. It is used by several major content aggregators and e-tailers (including Amazon.com, CDNow, Lycos and Bluefly) to facilitate personalized, dynamic, and customized shopping experiences. The Economist noted recently that "the true strength of Amazon.com lies in the wealth of information it now has about readers. Publishers would kill to have this information."

Newer technologies have enabled more sophisticated methods of consumer targeting. DoubleClick, a Web-based advertising company, uses customer profiles (built from a combination of site demographics, customer databases and buyer click-stream patterns) to send targeted advertising offers to people in real time. Other agents, such as the one used by Alexa.com, Dash.com and WiseWire, learn from and react to users' browsing patterns. Techniques are now being developed to mine these patterns of customer interaction, and use them to make customized price and product offers to Internet buyers (Dhar and Sundararajan, 1999). According to George Colony of Forrester Research, these 'killer clicks' will shape the Internet economy, and the balance of market power will tip towards players that understand and harvest this new source of information.

The success of companies that were early adopters of agents like Firefly and NetPerceptions suggests huge potential gains for that the companies who lead the way in developing and adopting more advanced demand agents. Certainly, dynamic pricing on the Internet is gaining increased attention in corporations (Datta and Segev, 1999), and is also being demanded by consumers. As reported by Business 2.0: "..according to a Jupiter survey in mid-1998, 80 percent of consumers expressed price elasticity as one of their top considerations in on-line buying decisions. This fact, coupled with the power of comparison shopping technologies such as Amazon.com's Junglee Canopy or Excite's Jango, are compelling reasons for on-line merchants to invest in and develop rapid-response pricing mechanisms." (Singh, 1999). In a recent report on agent-driven marketplaces, Wired Magazine profiled Charles Plott of Caltech, who experiments with markets that can manipulate both products and price in real time. According to Plott, in agent-driven markets, "..what is being sold is simultaneously being crafted with the price." There are numerous other markets being developed at leading companies, such as Jeff Kephart's simulated system of intelligent agents, that can infer buyer preferences and negotiate prices dynamically (Bayers, 2000). In their March 2000 Internet market strategies report, The Yankee Group, an influential e-commerce research firm predicts that most shopping agents ('bots') will soon incorporate dynamic pricing technology (Yankee Group, 2000).

When an intelligent agent actively infer buyer preferences and valuations, the crucial concern for the consumer is whether they want to give up their personal information in exchange for a better product offering. The source of their concern is two-fold. Trade-press attention has focused primarily on the more immediate issue of personal privacy — according to Weise (1997), "lying when Web sites ask for personal information is a common tactic to protect privacy. But on such sites, it destroys the quality of the recommendations you receive. Answer honestly, and these sites quickly learn a great deal about what you read, listen to and like to watch. Whether users will be willing to trade information about themselves for a more personal experience on-line remains to be seen". These concerns about privacy have been heightened recently, in light of the perceived misuse of browsing patterns, download histories and personal information, by companies like RealAudio and DoubleClick[2].

However, an equally important trade-off for the consumer is between the price paid in a dynamic pricing environment, and the level of customization obtained. Put simply, the more a demand agent infers about one's ideal product, the more it will know about one's willingness-to-pay. Intuitively, it appears that this kind of agent technology is likely to help sellers extract more value from their buyers. However, it is possible that consumers may change their behavior and choices in a manner that counters these potential losses in consumer surplus. It is not clear what aspects of these agents will be valuable to sellers, given that consumers will be making these price-product trade-offs. The welfare implications of these inferencing technologies in an electronic market are not intuitively evident. We address these issues in this paper. Broadly, we ask the following questions:

- In an electronic market, how does the presence of intelligent agents that can infer buyer preferences affect product pricing and consumer choices?
- What are the relative benefits of intelligent agents to buyers and sellers, in a market where consumer have heterogeneous valuations for products, and value product customization and quality differentially?
- Given these relative benefits to buyers and sellers, what characteristics of these agents are likely to benefit sellers, consumers or both?

Our paper adds to the growing body of literature on the economics of electronic markets and information goods. Most research on electronic markets has focused primarily on buyer search (Bakos, 1997) and pricing (Arunkundram and Sundararajan, 1998, Brynjolfsson and Smith, 1999, Clemons, Hann and Hitt, 1999). By examining simultaneous seller search and pricing, this paper builds on both these research streams. The results of the paper also relate to allied research in the pricing and customization of information goods (Mendelson and Jones, 1998, Bakos and Brynjolfsson, 1999, Hitt and Chen, 1999), online auction-based dynamic pricing (Vakrat and Seidmann, 1999) and to work in electronic market structure (Kambil and van Heck, 1998, Weber, 1998) and emergent business models in electronic commerce (Barua et al.,1999). It contextualizes work done on agent-based technologies (Bui and Lee, 1999, Provost, Jensen and Oates, 1999) to a dynamic pricing setting. It also enhances streams of literature related to price discrimination (Layson, 1994, Schmalensee, 1981), horizontal and vertical product differentiation (Chamberlain, 1953, Lancaster, 1975), and the relationship between competition, quality and pricing (Banker et al., 1998)

The rest of the paper is organized as follows. In Section 2, we provide an overview of our model, and explain its parameters through a simple example. Section 3 presents our main analytical results, which describe consumer and seller behavior, for a fairly general electronic market in which pricing

[2]This observation is all the more interesting, given the analogy between current corporate reactions to protecting privacy on the Web, and our paper's predictions - we return to this point in Section 5.

is driven by an intelligent agent. Some preliminary implications of these results are illustrated in this section. In Section 4, we use a specific set of functional forms to describe agent inferences, and use these to analyze the revenue and welfare implications of these agents, for different types of products, consumers and agent inference rates. Section 5 discusses the business implications of these results, and concludes the paper with a summary of our ongoing research.

2 Model Overview

We model an electronic market with one representative seller. The seller sells highly customizable products, and is a price setter. The market consists of several buyers, each of whom wishes to buy one unit of this customizable product. The seller uses an intelligent agent, which can make imperfect inferences about the true valuations of these buyers, based on an exogenous analysis of the buyers' specifications of the product attributes that they want. Customization is costless, and the seller has the ability to price the product differently for each buyer.

Each buyer has an ideal product — a set of product specifications that meet the buyer's needs optimally. Different buyers may have different ideal products. The buyer has a specific valuation v for this ideal product, and the value of the product to the buyer is reduced if she fails to get her ideal product. We term this reduction in value the *cost of commoditization* borne by the buyer when the product that she buys is not perfectly customized. The greater the extent of commoditization (i.e., the greater the deviation of product specifications from a buyer's ideal product), the higher the cost of commoditization. The seller also sells generic products, which are of lower value to all buyers than any customized product, and possibly of zero or negative value to some.

The buyers in our model differ in their tastes and valuations. The seller does not know what an individual buyer's valuation is (before the intelligent agent is used). However, the seller knows that overall, buyer demand is downward sloping in price. The seller also knows the unit cost of commoditization that the buyers bear. As the buyer requests higher degrees of customization, the product specifications come closer and closer to those of the buyer's ideal product, thereby reducing the cost of commoditization borne by the buyer.

However, when a buyer chooses a particular level of customization, and lets the seller know the product specifications corresponding to this level of customization, the seller's intelligent agent uses this information to make an inexact inference about the buyer's valuation, and provides the seller with an interval estimate of this valuation. The interval estimate provided by the agent always contains v, thereby ensuring that our intelligent agent is indeed intelligent. The seller cannot infer anything else about v from this interval estimate (which would not be the case, for instance, were we to assume that v is the mean of the interval). We are therefore also precluding strategic inferences by the seller, based on buyer choices. We discuss the justification for this assumption in Section 3.

When the level of customization chosen by the buyer is zero – that is, when the buyer chooses the generic product – the width of the intelligent agent's interval estimate is the highest[3]. Additional units of information, i.e., higher levels of customization, or more precise product choice specifications, result in progressively lower levels of error in the agent's inferences, and consequently, narrower interval estimates. When the buyer reveals all of the specifications of their ideal product, the intelligent agent has the maximum possible information, and can therefore make the most accurate estimate of the buyer's valuation. The buyer must therefore make the trade-off between getting closer to her ideal product, and paying a price which gives her less surplus. This trade-off is illustrated in Figure 1.

[INSERT FIGURE 1 HERE]

We assume that the buyer is not making inferences about the intelligent agent's behavior from past prices quoted. When the buyer chooses a customization level, all that she knows is that the intelligent agent will provide the seller with an interval that contains v. She also knows the width of the interval, but does not know what the actual interval is going to be. Since the buyer knows the width of the interval that corresponds to each level of customization, a choice of a level of product customization by the buyer is equivalent to a 'choice' of interval width by the buyer. To illustrate these points more clearly, we introduce our model's parameters and notation.

2.1 Notation and Model Description

- v : Buyer valuation of ideal product.
- m : Level of customization chosen by the buyer. $m \in [0, 1]$. $m = 0$ implies a choice of the generic product, and $m = 1$ implies a choice of the buyer's ideal product.
- t : Unit cost of commoditization. A choice of a level of customization m results in a cost of commoditization $t(1-m)^2$, and a net value of $v - t(1-m)^2$ to the buyer.
- $\theta(m)$: Width of the interval estimate of a buyer's valuation by the intelligent agent, when the buyer's level of customization is m. $\theta'(m) < 0$, $\theta''(m) \geq 0$.
- $\theta_{\max} = \theta(0)$: Width of the interval estimate, in the absence of any product specification information.
- $\theta_{\min} = \theta(1)$: Width of the interval estimate, when the buyer chooses her ideal product.
- ε : Lower support of the interval estimate.
- $m(.)$: Functional inverse of $\theta(.)$.

[3] An implied assumption is that the seller can make some sensible inference (i.e. has a prior) about the buyer's valuation, even in the absence of buyer specifications — possibly from a demographic profile, or a zip code match.

- $m(\theta)$: Level of customization corresponding to an interval width θ. $m'(\theta) < 0$, $m''(\theta) \geq 0$.
- $\tau(\theta)$: Cost of commoditization borne by the buyer choosing a level of customization corresponding to an interval width θ. $\tau(\theta) = t(1 - m(\theta))^2$.
- $p(\theta)$: Price expected by the buyer choosing a level of customization corresponding to an interval width θ. $p(\theta)$ is a random variable, not an average value.
- $f(p)$: Density of $p(\theta)$.
- p^* : Price chosen by seller
- $\psi(\theta)$: The net consumer surplus expected by the buyer when choosing a customization level corresponding to an interval width θ.

The sequence of events we model is as follows:

1. The buyer and seller both start out knowing the buyer's unit cost of commoditization t.
2. The buyer chooses a level of customization m. The buyer's valuation for this product is $v - t(1-m)^2$.
3. Based on this choice m by the buyer, the intelligent agent provides the seller with the estimate that the buyer's valuation v (for her ideal product) lies in $[\varepsilon, \varepsilon + \theta(m)]$. Clearly, ε can take values only in $[v - \theta(m), v]$, since we have assumed that v will definitely be in $[\varepsilon, \varepsilon + \theta(m)]$. Two possible instances of this 'sliding window' estimate $[\varepsilon, \varepsilon + \theta(m)]$ of the intelligent agent are illustrated in Figure 2 (a)
4. Based on the estimate that v could lie anywhere in $[\varepsilon, \varepsilon + \theta(m)]$, with equal probability on all points in the interval, the seller sets a price p^*.
5. If the net surplus to the buyer at this price, which is $(v - t(1-m)^2 - p^*)$, is non-negative, the buyer purchases the product, and the seller gets revenues p^*. If not, both the buyer and seller get zero value.

[INSERT FIGURE 2(a) HERE]

We assume that every increase in customization m chosen by the buyer results in a *strict* increase in the accuracy of the agent's estimate. In other words, $\theta(m)$ is strictly decreasing in m. This implies that it is invertible, and, with a little abuse of notation, we denote $m(.) = \theta^{-1}(.)$. As mentioned earlier, since the buyer knows the width of the interval $\theta(m)$ that corresponds to each level of customization m, a choice of m is equivalent to a choice of interval width. Since $\theta(.)$ is strictly monotonic, this correspondence is one-to-one — each choice of m corresponds to a unique interval width, and vice versa. Throughout the paper, we therefore model the buyer's choice of a level of customization m as being equivalent to the buyer 'choosing' a interval width[4] θ such that $m(\theta) = m$.

Correspondingly, the cost of commoditization for a 'choice' of θ by the buyer is $\tau(\theta)$. Since the cost of commoditization is $t(1-m)^2$,clearly, $\tau(\theta) = t(1-m(\theta))^2$. The choice of the functional form $t(1-m)^2$ is motivated by the fact that our cost of commoditization is analogous to a 'transportation cost' in economic models of horizontally differentiated products, $1 - m(\theta)$ is analogous to the 'distance' from the consumer's ideal product in these models, and the quadratic cost function is a widely used form in such models.

Possible relationships between m and θ are illustrated in Figure 2(b). We assume that every additional 'unit' of information revealed by the buyer is likely to have a lower or equal marginal impact on the accuracy of the estimate, as compared to the previous 'unit' of information. In other words, $\theta(.)$ is convex. Studies of the rate at which agents learn from data have typically confirmed this intuitively appealing notion of diminishing returns to information (see, for instance, Provost, Jensen and Oates, 1999, or Frey and Fisher, 1999). Clearly, the more convex $\theta(m)$ is, the less information is needed by the intelligent agent to provide the seller with an interval of the same width. Therefore, the convexity of $\theta(.)$ is, in a sense, a measure of how good the agent's inferencing technology is.

[INSERT FIGURE 2(b) HERE]

Since $\theta'(m) < 0$ and $\theta''(m) \geq 0$, this implies that $m'(\theta) < 0$ and $m''(\theta) \geq 0$. Also, $m(\theta_{\max}) = 0$, and $m(\theta_{\min}) = 1$. If one mentally transposes Figure 2(b), it is clear why these results are true.

2.2 Overview of buyer's problem

The sequence of information that each party (the buyer and seller) has at each decision stage is summarized below.

[4] While the buyer can choose the width of the interval (through her choice of a level of customization), she cannot choose the actual interval. For instance, a buyer who values a product at $25 may choose a level of customization that induces an interval width of 5. This can result in the IA, choosing the interval as [23, 28] (which contains the buyer's valuation) or as [24, 29] (which also contains the buyer's valuation). In other words, the buyer's choice of an interval width gives her no control over the actual endpoints of the interval.

Event	Buyer knows	Seller and IA know
Buyer is endowed with v	$v, \tau(.)$	$\tau(.)$
Buyer chooses θ	$v, \theta, \tau(\theta)$	$\tau(.)$
Buyer reveals choice of θ to seller	$v, \theta, \tau(\theta)$	$\theta, \tau(\theta)$
Intelligent agent gives seller interval estimate $[\varepsilon, \varepsilon+\theta]$	$v, \theta, \tau(\theta)$	$\theta, \tau(\theta), [\varepsilon, \varepsilon+\theta]$
Seller chooses and reveals price p^*	$v, \theta, \tau(\theta), p^*$	$\theta, \tau(\theta), [\varepsilon, \varepsilon+\theta], p^*$

When the buyer reveals her preferences to the extent corresponding to the customization level $m(\theta)$, all that she knows is that the intelligent agent will provide the seller with an interval $[\varepsilon, \varepsilon+\theta]$ that contains v. She does not know what the actual value of ε is going to be. Depending on the value of $\tau(\theta)$, the buyer forms some sensible prior buyer has on ε, with support $[v-\theta, v]$. This prior of ε causes the buyer to form a corresponding prior on the price that the seller will set. We denote this price that the buyer expects as $p(\theta)$. In order to compute the prior on $p(\theta)$, the buyer 'solves' the seller's pricing problem for each value of $\varepsilon \in [v-\theta, v]$, and estimates the price that she will face at that level of customization. Having computed the distribution of possible prices for a choice θ, the buyer then chooses the θ that maximizes expected consumer surplus $\psi(\theta)$, which is:

$$\psi(\theta) = E[\max(v - p(\theta) - \tau(\theta), 0)],$$

since the buyer does not expect to buy at prices that result in negative surplus. The expectation is taken over the buyer's prior on $p(\theta)$, which is induced by the buyer's prior on ε.

2.3 Illustration

To illustrate our model of customization and agent inference, consider the following example. This purpose of this example is to explain our model — the actual dynamics of customization and pricing at the company mentioned may be different.

Customdisc.com is an Internet music service that allows individuals to create their own personalized compact discs. The service features over 250,000 songs from a wide variety of eras and musical genres. A well structured site enables easy navigation, making it easy for customers to find music that fits their tastes exactly. A customer can create her ideal CD with exactly the songs of her choice, complete with one's own title and cover art. Customdisc.com charges different prices depending on the choices made by each customer. In addition, the site offers generic collections of songs which a buyer could choose. The firm uses personalization agents to make inferences about its customers based on individual profiles and past buyer choices.

Each CD is, therefore, a highly customizable product. The *ideal product* ($m = 1$) for each buyer is a CD containing exactly the songs the buyer wants. The generic product ($m = 0$) is any

CD with one of the generic collections of songs. Also, a buyer could choose an intermediate level of customization m, by resorting to a combination of unique choices and standard compilations provided by the seller. For instance, a buyer wishing to compile a 70-minute CD of sentimental country favorites, could handpick each song (one from each of her favorite artists) for her CD or choose a combination of a few tracks that she is particularly interested in and an assorted bundle of country/folk tracks recommended by the seller. In the latter case, the product is no longer the buyer's ideal product and a buyer opting for partial customization suffers a cost of commoditization. As mentioned earlier, the only way a buyer can receive her ideal product is to individually select all the tracks that would constitute her CD.

Based on the choices made by these buyers, Customdisc is able to obtain an interval estimate of their valuations. Consider a buyer who is choosing a CD of 10 songs from Customdisc's selection of 1960's folk music tracks, and who values her ideal product at \$25. This would correspond to $v = \$25$. If this buyer chooses all the songs that he or she wants ($m = 1$), Customdisc's intelligent agent is able to infer her valuation within a margin of \$2 (or $\theta_{\text{min}} = 2$). A sample interval estimate here would be that the buyer's valuation for the buyer's ideal product is in $[\$23.50, \$25,50]$ (which would correspond to $\varepsilon = \$23.50$).

On the other hand, if this buyer were to purchase a pre-complied assorted collection of 60's folk songs ($m = 0$), the buyer's valuation is \$15. This means that $v - t(1-0)^2 = \$15$, or $t = \$10$. Also, suppose that in this case, the agent, which has much less information, can only infer her valuation within a margin of \$5. (which means that $\theta_{\text{max}} = 5$). A sample estimate of the buyer's valuation v here is that v is in $[\$23, \$28]$. Remember that v is the valuation the buyer has for her *ideal* product. Consequently, the seller knows that the buyer will be willing to pay between \$13 and \$18 for the generic product.

If the buyer hand-picks, say, 5 out of 10 tracks, and chooses a pre-compiled set of 5 others (for simplicity, let's say that this corresponds to $m = \frac{5}{10}$), suppose the intelligent agent can estimate v within a margin of \$3 (which makes $\theta(\frac{5}{10}) = 3$). A sample interval estimate here would be $[\$23, \$26]$. The buyer's cost of commoditization for this partially customized product is $t(1 - \frac{5}{10})^2 = \$2.50$, which means that $\tau(3) = \$2.50$ ($\theta = 3$ is the width of the interval 'chosen' by the buyer through her choice of $m = \frac{5}{10}$).

Consequently, the seller knows that the buyer would be willing to pay between (\$23 − \$2.50) and (\$26 − \$2.50), or between \$20.50 and \$23.50 for this partially customized product. The buyer's true valuation for this partially customized product is, of course, \$25 − \$2.50 = \$22.50.

Note here that m refers to a level of customization, not a specific product. *Two buyers who get the same level of customization are not buying the same product — they are merely buying products which are at the same 'distance' from their ideal product.* It is precisely this difference in buyers' ideal products that makes it possible for the intelligent agent to make inferences about the buyers' valuations, based on their product specifications. For instance, a buyer who chooses a rare classic from 1913, and another who chooses the latest single by Britney Spears, could both be getting the same level of customization. However, their valuations v could be very different. In addition, a buyer who chooses a combination of (i) 8 of her favorite classical tunes and (ii) an assorted bundle of rare classics provided by the seller, and another buyer who chooses a combination of (i) 8 of her favorite jazz tunes and (ii) an assortment of 1980's jazz tunes, are modeled as choosing the same level of customization m.

We have chosen this approach to modeling customization for three distinct, yet correlated, reasons. Firstly, while there is the assumption of an inherent underlying model of product differentiation (and a corresponding mapping from different products to valuation intervals), treating differentiation as implied, instead of explicitly, enables us to capture all the essential details of the inferences made by the intelligent agent, without explicitly considering a finite number of product dimensions, which only complicates the analysis unnecessarily. Secondly, the focus of our model is not on product differentiation — it is on the pricing, consumer choice and welfare implications of inferences made by an intelligent agent about buyers' underlying valuations, given that buyers who have certain attribute preferences (and therefore a preference for particular instances of the differentiated product) have valuations that are associated with their product attribute preferences. Finally, using a continuum of values for customization is more general than restricting the model to n different product dimensions, and also enables us to use continuous optimization techniques that would not be applicable to a discrete choice setting.

3 Analysis: Preference revelation and pricing

We model the intelligent agent as choosing an interval which satisfies the following three criteria, given a value of θ:

- The interval is of width θ
- The interval contains v
- The lower bound[5] of the interval ε is such that $\varepsilon \geq \tau(\theta)$.

Both the intelligent agent and the buyer know the functional form of $\tau(.)$, and therefore, when the buyer reveals her choice of θ, the value of $\tau(\theta)$ is common knowledge. A rational buyer would not choose θ such that $\tau(\theta) > v$, since this leaves the buyer with no surplus, even with a price of zero. We assume that there is no other valuation-related information that could change the seller's prior about what the actual value of v is; all of this information is contained in this interval provided

[5] One may conjecture that the agent could operate differently - that it may actually simply choose $\varepsilon \in [v - \theta, v]$, and then narrow it's interval if $\varepsilon < \tau(\theta)$. We investigate this in Appendix B, and show that it does not change the optimal buyer choices predicted by Proposition 4 (and consequently, does not change any of our subsequent results).

by the intelligent agent. Specifically, an assumption we are making here is that the seller and IA do not make any additional strategic inferences about the buyers valuation from the buyer's choice of θ. If any such inferences are made, we assume that they are subsumed by the fact that the interval returned is $[\varepsilon, \varepsilon+\theta]$. This is an unusual assumption, and requires some explanation. Mathematically, it is in fact possible to analyze a pure signaling model, where buyers signal their valuations, sellers make valuation inferences from these signals, and these inferences are imperfect (i.e., the buyers' strategies yield pooling equilibria). However, this approach presumes all information exchange as being purely strategic, when in fact, intelligent agents make their inferences based on past product choices, click-stream data and demographic data, rather than on strategic buyer representations.

A hybrid model (which factors in both strategic information and 'noise'), apart from being difficult to analyze, shifts the focus of the model towards the inference process, and away from the implications of the inferences. Besides, there is literature in the trade press that suggests that a variety of intelligent agents — knowledge-based agents that can reason under uncertainty, goal-driven agents that can plan, and agents that learn — are most often constructed using one or more of the following artificial intelligence technologies – artificial neural networks, fuzzy logic, and/or genetic algorithms (Fingar, 1999) . For instance, neural networks are used to construct intelligent agents that can learn interest profiles of Web surfers and serve them content based on their revealed preferences (Johnson, 1997). These technologies (especially neural- network-based agents) provide the seller with output after processing a series of inputs, but do not reveal the underlying functions that resulted in mapping the inputs to the output. This implies that these mechanisms function like a 'black box', and do not allow the deployer of the agent to observe the specific function that transformed the inputs into the output. This, in turn implies that the seller can get an estimate of the buyer's valuation within a window, but cannot actually see , control or even re-calibrate (explicitly) the process that led to the creation of the window.

Again, modeling the actual inference process of agents is not the intention of the paper. Besides, it seems clear that the actual inference process of intelligent agents is typically not known in practice. This motivates our choice of approach — modeling intelligent agents as non-strategic 'interval choosers'. It allows us to focus on our problem of interest — the changes in consumer behavior, the corresponding pricing and revenue implications, and the welfare effects of having agents that make imperfect inferences.

Therefore, the prior that the seller has is on the buyer's valuation for their ideal product is that v is uniformly distributed in $[\varepsilon, \varepsilon + \theta]$.

3.1 Optimal seller pricing

Based on the framework above, we now solve the seller's pricing problem. The mathematical proofs of all our results are in Appendix A.

Lemma 1 *If the estimate about the buyer's valuation that is provided by the seller (demand) agent is that the buyer's true valuation v is uniformly distributed in $[\varepsilon, \varepsilon+\theta]$, then the optimal price p^* for the seller is:*

$$
\begin{aligned}
p^* &= \frac{\varepsilon+\theta-\tau(\theta)}{2} \text{ if } \varepsilon \leq \theta+\tau(\theta) \\
p^* &= \varepsilon-\tau(\theta) \text{ if } \varepsilon \geq \theta+\tau(\theta)
\end{aligned}
$$

The intuition behind this pricing scheme is easily understood, and is illustrated in Figure 3. At a low enough interval width θ from the intelligent agent, the price is set to capture the sale, irrespective of the buyer's true valuation – at this level of information accuracy, the gains from closing the sale with certainty outweigh the losses from the lower price. However, as the level of error increases, the seller has to trade off the possibility of losing the customer with the reality of significantly lower revenues from pricing at a level that will make ensure that the sale takes place. The pricing problem becomes identical to that of a monopolist facing a set of customers whose composite demand function is linear and downward sloping, and the solution — pricing at half the upper bound on the distribution of valuation — is the familiar optimal monopoly price.

[INSERT FIGURE 3 HERE]

Having characterized the seller's behavior, we are now in a position to address the buyer's decision problem. This is significantly more complex, as the next few results will indicate. At specific values of ε and θ, the buyer knows that the seller sets prices according to the price schedule in Lemma 1. The buyer is also aware that the seller's intelligent agent forms an estimate on her valuation v. However, the buyer does not know the actual value of ε chosen by the intelligent agent. Consequently, the buyer 'second guesses' the agent, and forms an estimate on what the seller's estimate might be. This is consistent with our model of a rational buyer. It is also how we would prescribe that a *buyer agent* be programmed to behave.

The buyer knows that the intelligent agent would have chosen an ε such that $\varepsilon \leq v$, and also such that $\varepsilon \geq v-\theta$ and $\varepsilon \geq \tau(\theta)$. The buyer therefore expects ε to be distributed in $[\alpha, v]$, where $\alpha = \max[v-\theta, \tau(\theta)]$. There is no other information the buyer has about the agent's choice of ε, and so the buyer places equal probability on each value in this interval. Consequently, the buyer's prior on ε is that it is uniformly distributed in $[\alpha, v]$. Note that the buyer knows whether $v-\theta$ is higher or lower than $\tau(\theta)$ – the seller, on the other hand does not – she is just given a value of ε.

3.2 Optimal buyer choices

Given this prior on ε, the price distribution the buyer expects at a particular value of θ (corresponding to a degree of Customization m chosen by the buyer) is derived in Proposition 2.

Proposition 2 *The buyer's prior distribution over the price p set by the seller, at a level of customization $m(\theta)$ that induces an error θ, has a density function $f(p)$ which is as follows:*

(a) If $\theta \leq \frac{v-\tau(\theta)}{2}$: p is uniformly distributed in $[v-\tau(\theta)-\theta, v-\tau(\theta)]$, and $f(p)=\frac{1}{\theta}$ in this interval.

(b) If $\frac{v-\tau(\theta)}{2} \leq \theta \leq v-\tau(\theta)$: $f(p)$ has support $[\frac{v-\tau(\theta)}{2}, v-\tau(\theta)]$, and:

- $f(p)=\frac{2}{\theta}$ *for* $p \in [\frac{v-\tau(\theta)}{2}, \theta]$
- $f(p)=\frac{1}{\theta}$ *for* $p \in [\theta, v-\tau(\theta)]$

(c) If $\theta \geq v-\tau(\theta)$: p is uniformly distributed in $[\frac{\theta}{2}, \frac{v+\theta-\tau(\theta)}{2}]$, and $f(p)=\dfrac{2}{v-\tau(\theta)}$ in this interval.

Figure 4 illustrates the result of this proposition. In case (a), the buyer's prior on ε is such that ε is always in the range of values for which it is optimal for the seller to charge the latter price of Lemma 1. Hence, the prior of the buyer on price is simply the prior on ε shifted to the left by $\tau(\theta)$. In case (c), the same logic applies, but for the former price of Lemma 1. Since the former price admits a lower range of prices for the same range of ε, the buyer's prior on price has a narrower support, and more density on each point of this support. In case (b), either the former or the latter price is possible, depending on the value of ε.

[INSERT FIGURE 4 HERE]

Note that $\theta+\tau(\theta)$ is an increasing function of θ so long as $\tau(\theta)$ is non-decreasing, and therefore, these successive intervals correspond to increasing values of θ. This is formally established in the proof of Lemma 3.

The buyer's decision problem is to choose the level of $m(\theta)$ that maximizes her surplus $\psi(\theta)$ At any price $p(\theta)$, recall that the buyer's surplus is either $v-p(\theta)-\tau(\theta)$, if $v-\tau(\theta) \geq p$, or is zero if $v-p(\theta)-\tau(\theta) \leq p$, since the buyer does not purchase. Therefore, the buyer's expected surplus $\psi(\theta)$ is the expected value of $\max[v-p(\theta)-\tau(\theta), 0]$, with the expectation taken over the buyer's distribution over price $p(\theta)$. The actual values of the buyer's surplus are derived in Lemma 3, and the buyer's optimal choice of product customization is characterized in Proposition 4.

Lemma 3 *If the buyer chooses a level of customization $m(\theta)$, with a corresponding interval width θ, then the expected surplus $\psi(\theta)$ of the buyer is:*

(a) If $\theta \leq \frac{v-\tau(\theta)}{2}$, then $\psi(\theta)=\psi_1(\theta)=\dfrac{\theta}{2}$;

(b) If $\frac{v-\tau(\theta)}{2} \leq \theta \leq v-\tau(\theta)$, then $\psi(\theta)=\psi_2(\theta)=v-\tau(\theta)-\dfrac{\theta}{2}-\dfrac{[v-\tau(\theta)]^2}{4\theta}$;

(c) If $v-\tau(\theta) \leq \theta \leq 2[v-\tau(\theta)]$ then $\psi(\theta)=\psi_3(\theta)=\dfrac{(2[v-\tau(\theta)]-\theta)^2}{4[v-\tau(\theta)]}$, and

(d) If $\theta \geq 2[v-\tau(\theta)]$, then $\psi(\theta)=0$.

Part (a) of Lemma 3 indicates that for high values of m (or low values of θ), decreasing customization (or increasing θ) actually benefits the buyer, since the buyer's surplus increases linearly in θ. Intuitively, this is a consequence of the fact that at very high levels of customization, the seller 'knows too much' about the buyer's valuation to make near-perfect customization worthwhile.

The expressions for the other surplus terms in Lemma 3 do not lend themselves to intuitive interpretation without further analysis, and therefore, having established what the buyer's expected surplus will be, as a function of θ, Proposition 4 examines what the optimal choice of θ will be. This is a crucial proposition of the paper, since it proves (with no additional restrictions on the functional form on the buyer's cost of commoditization $\tau(\theta)$, or the agent's inference function θ) that buyers will almost always choose the 'middle ground', rather than opting for the ideal product, or the generic product. It also shows that buyers *never* choose their ideal products.

Proposition 4 *The buyer chooses a level of customization $m(\theta^*)$ which induces an interval width θ^* such that:*

(a) If $\theta_{\max} \leq \frac{v-\tau(\theta_{\max})}{2}$, then $\theta^* = \theta_{\max}$.

(b) If $\theta_{\max} > \frac{v-\tau(\theta_{\max})}{2}$, then θ^* is the solution to the following optimization problem:

$$\max_{\theta \in \Re^+} \psi_2(\theta) = v - \tau(\theta) - \frac{\theta}{2} - \frac{[v-\tau(\theta)]^2}{4\theta},$$

subject to:

$$v - \tau(\theta) \leq 2\theta,$$
$$v - \tau(\theta) \geq \theta.$$

The buyer always makes a choice such that the constraints are non-binding. Furthermore, if the technology $\theta(m)$ of the seller's intelligent agent is such that $\tau(\theta)$ is convex (i.e., if $\tau''(\theta) \geq 0$), then the unique optimal choice θ^* of the seller solves $\psi_2'(\theta) = 0$.

The results of Proposition 4 are illustrated in Figure 5. As mentioned earlier, at low values of θ (i.e., values of θ less than θ_1) which correspond to high values of m, and consequently, products close to the buyer's ideal product, the price set by the intelligent agent is very close to the buyer's true valuation, since the margin of error θ in the agent's estimate is fairly low. Intuitively, when the buyer decreases her level of customization, she gets a better price, but also gets a worse product. The fact that surplus increases monotonically shows that the price effect dominates in this region – in other words, at high levels of customization, the gains from a better price strictly outweigh the losses from a less suitable product. This causes the buyer to steadily increase the level of interval width, and confirms that the buyer never chooses her ideal product, however poor the agent's inferences are.

[INSERT FIGURE 5 HERE]

On the other extreme, for fairly high values of θ (i.e., values of θ greater than θ_2), the buyer's surplus is strictly decreasing as the width of the agent's interval increases, or as the level of customization decreases. In this region, the price the buyer expects displays an interesting trend. For the seller, a higher value of θ corresponds to less precise estimates from the intelligent agent, and a higher level of uncertainty about the buyer's true valuation. This helps the buyer to some extent, since the seller is likely to price away from the buyer's true valuation, and the buyer could benefit from the increased surplus.

However, higher uncertainty also causes the seller to price too high in a certain percentage of the cases. Consequently, the buyer is shut out of the market in these cases, and gets no surplus at all. This reduces the desirability of higher values of θ to some extent — this, coupled with the fact that there are steadily increasing consumer surplus losses from a less customized product results in surplus strictly decreasing in the region from which θ is greater than θ_2. This effect of getting 'shut out' is likely to affect buyers at the lower end of the market more than those at the higher end, and we will return to this point in Section 4.

The buyer is therefore pushed towards the middle. Facing the trade-off between better prices and better products, Proposition 4 shows that the buyer almost always finds herself in the region $[\theta_1, \theta_2]$. The latter part of the proposition simply establishes when the corresponding optimization problem has a well-behaved objective function, that yields a solution one can explicitly solve for.

Part (a) or Proposition 4 has some interesting implications as well. $\theta_{\max}$ is also, in some sense, an inverse measure of how good the intelligent agent's technology is. This part of the proposition establishes that it the agent's worst estimate is too accurate, then buyers are less likely to customize at all. Since the right hand side of the inequality increases linearly in v, this indicates that in these cases, higher valuation customers are likely to customize less often than lower valuation customers. This observation is investigated further in Section 4. Before we do this, however, we solve for the seller's expected profit when selling to a buyer with valuation v.

Proposition 5 *If the buyer's optimal choice is θ^*, the seller's expected revenues $\pi(\theta^*|v)$ from a buyer of valuation v, are given by:*

(a) If $\theta_{\max} > \frac{v-\tau(\theta_{\max})}{2}$, then

$$\pi(\theta^*|v) = \frac{\theta^*}{2} + \frac{(v-\tau(\theta^*))^2}{4\theta^*}.$$

(b) If $\theta_{\max} \leq \frac{v-\tau(\theta_{\max})}{2}$, then

$$\pi(\theta^*|v) = \frac{2v+\theta^*-2\tau(\theta^*)}{4}.$$

Proposition 5 illustrates an interesting point. Both functional forms for π indicate that it is not clear whether seller revenues increase with lower choices of θ (or better information about the buyer). It introduces the possibility that better agent technologies may not always be better for sellers. In case (b), in fact, the seller's revenues are strictly increasing in $\theta_{\max}$, since Proposition 4 tells us that in this case, $\theta^* = \theta_{\max}$, and at this value of θ^*, $\tau(\theta^*)$ is a constant. However, these results are for fixed values of v, which are not known ex-ante, and therefore, the seller may not benefit from increasing $\theta_{\max}$, since it is technologically unlikely that one could increase $\theta_{\max}$ without increasing θ across the board, and it is not clear ex-ante whether the condition $\theta_{\max} \leq \frac{v-\tau(\theta_{\max})}{2}$ may actually be satisfied.

Note that these results (apart from the uniqueness of $\psi'(\theta) = 0$) are valid for any specification of $\theta(.)$ that is decreasing and convex – properties that are both intuitively appealing, and that are almost universally true in practice for agents that learn from data. However, further analysis of the buyer's choices are needed to make stronger statements about the revenue and welfare effects of these intelligent agents, and these require us to choose concrete functional forms for $\theta(.)$, which we do in Section 4.

4 Results

In order to gain further insight into the market transformation caused by intelligent demand agents, and the resulting nature of consumer surplus and seller profits, we focus on a family of agent technologies, characterized by the inference function $\theta(m) = (1-m)^k$, for a range of values of $k \geq 1$. These satisfy the properties of $\theta(.)$ that we discussed in section 2 as being representative of agent technologies. They also all yield the same range of values of θ ($\theta_{\min} = 0$, $\theta_{\max} = 1$), which allows us to sensibly compare buyer choices and seller profits across different values of k (which is a measure of the rate at which the demand agents infer, as a function of the information that they are provided by the buyer). If one refers back to Figure 2(b), the more steeply convex curves correspond to higher values of k.

We begin with $k = 2$, since this generates functional forms that yield closed-form solutions.

Proposition 6 *If $\theta(m) = (1-m)^2$, then for a given level of v and t:*

(a) For a buyer with valuation v and unit commoditization cost t, the optimal level of customization $m(\theta^*)$ chosen by the buyer induces an interval width $\theta^*(v,t)$ such that:

$$\theta^*(v,t) = \frac{v}{\sqrt{2+4t+t^2}}.$$

(b) The resulting consumer surplus is

$$\psi^*(v,t) = \frac{\left(2+t-\sqrt{2+t\,(4+t)}\right)v}{2}.$$

(c) The seller's expected revenues are.....

$$\pi^*(v,t) = \frac{v\left[(2+t\,(2+t)) - t\sqrt{2+t\,(4+t)}\right]}{2\sqrt{2+t\,(4+t)}}.$$

The proof of this proposition involves a direct application of Proposition 4, using the specific functional form for the agent's inference rate $\theta(.)$. Some comparative statics are discussed after the next result:

Corollary 7 *At the buyer's optimal level of customization:*

(a) the buyer's consumer surplus is increasing in v, and decreasing in t.

(b) the seller's profits are increasing in v, and decreasing in t.

Therefore, surplus and profits are higher for/from higher valuation customers, and lower for customers with higher costs of commoditization. What this confirms is that for the rate of inference $k = 2$, the fortunes of the buyer and the seller move in tandem. However, examining the expression for interval width in Proposition 6(a) indicates that the width of the interval estimate 'chosen' by the buyer is increasing in v — or, in other words, as the value a buyer places on their ideal product increases, the final product they choose is further and further away from that ideal product.

Figures 6 through 8 further illustrate[6] the results of Proposition 6 and Corollary 7. Figure 6 summarizes the shape of the surplus function $\psi(v,t)$ in its two arguments v and t. It confirms that ψ is increasing in v and decreasing in t. Since the curves are progressively closer together along the t–axis as v increases, the figure also indicates that a unit increase in the cost of commoditization t has a more negative marginal surplus impact on a higher valuation customer. In other words, high valuation customers are more adversely affected by increases in the cost of commoditization, an observation confirmed by the fact that the cross-partial of ψ with respect to v and t is negative.

[INSERT FIGURE 6 HERE]

Also, successively higher surplus curves (i.e., iso-curves for which the ψ values are higher) are increasingly steep. This shows that the marginal impact of an increase in t increases relative to the marginal impact of an increase in v. In other words, buyers whose optimal choice endows them with a higher consumer surplus are increasingly more sensitive to increases in the cost of commoditization, relative to the valuation they place on their ideal product.

Finally, the iso-curves are progressively lower and further apart as t decreases, indicating that surplus is convex in cost of commoditization. The fact that the curves are slightly concave indicates that the surplus curve is jointly (weakly) convex in v and t.

Corollary 7 shows that the revenues of the seller and the surplus of the buyer move in similar directions, when v and t change. Figure 7 strengthens this observations, by indicating that the shape

[6] The iso-function curves of Figures 6 through 8 are a succinct way of depicting the rate of change and shape of a function of two variables. Iso-profit curves are commonly used in economic analysis; our iso-surplus and iso-product curves are loosely analogous to indifference curves.

The curves are plotted by projecting the iso-(v,t) points (i.e., points on the function's surface which have equal values of the function) onto the (v,t) plane.

of ψ and π are very similar. The seller's revenues are more sensitive to the cost of commoditization at higher values of buyer valuation and at higher revenue values. Also, revenues are jointly (weakly) convex in v and t, in the region plotted.

[INSERT FIGURE 7 HERE]

It is also worth observing that the seller profits are a little over twice the buyer surplus.

Figure 8 illustrates how optimal customization levels chosen by the buyers vary with buyer valuation and cost of commoditization. This figure illustrates the stark trade-off between withholding personal information in order to get a better price, and revealing this information in order to get a better product. Clearly, as v decreases and t increases, the optimal level of customization increases. This is because as ideal product valuation v increases, at a constant cost of commoditization t, the buyer gains more at the margin from withholding information (from a better price) than she loses (due to a less customized product); hence, the choices of product become increasingly commoditized for higher valuation buyers.

[INSERT FIGURE 8 HERE]

This behavior leads to a curious effect, which is discussed further in Section 5. Since the product choices of higher valuation buyers are affected more adversely than those of lower valuation buyers, intelligent demand agents may actually bring about more buyer surplus equality by effectively causing a 'transfer of surplus' from high valuation to low valuation buyers.

It is possible that this effect (of higher valuation buyers choosing inferior products) is a consequence of the fact that t is constant across buyers. We therefore explore the implications of varying t with valuation[7], and simultaneously investigate the effects of varying the inference rate of the intelligent agent. To achieve the latter, we solve the optimization problem of Proposition 4 for values of k varying between 1 and 3 (with our analytical case $k = 2$ as the midpoint – as it turns out, other values of k do not yield closed-form expressions for m, ψ or π, so we used numerical optimization to solve these cases). We chose $k = 1$ as the lower limit, since it describes a situation where the agent's error is linear in the level of customization chosen.

Figures 9 and 10 illustrate some of the results of our analysis. As expected, increasing the rate of inference of the intelligent agent made the buyer's surplus increasingly lower. What was initially surprising was that the same effect was observed for seller revenues — a higher rate of agent inference, rather than helping the seller, actually reduced the seller's revenues steadily. This result held across a wide range of v and t values – we have depicted two sample ranges in Figures 9 and 10.

[7] We have analytically solved a model where v and t are perfectly correlated. This assumption increases seller-side uncertainty, and also reduces our ability to isolate differentially the effects of the two parameters. Our analysis is available on request, in a technical appendix.

[INSERT FIGURES 9 AND 10 HERE]

This result seems fairly counter-intuitive, until one examines the level of customization charts in Figures 9(b) and 10(b), and relates them to the total surplus charts of Figure 9(d) and 10(d). Note that total surplus (which is the sum of the seller revenues and buyer surplus, and is, in effect, the total 'value' created from the transaction) is simply $v - \tau(\theta^*)$ – the total value of the product to the buyer, at a customization level corresponding to the optimal interval width θ^* chosen by the buyer. Of this, an amount equal to the price charged is transferred to the seller. As indicated in Figures 9(b) and 10(b), since the optimal level of customization chosen by the seller drops dramatically as the agent's ability to make inferences improves, so does the total 'size of the pie' – the total surplus $v - \tau(\theta^*)$ – that the buyer and seller split. The revenue results simply indicate that the buyer adjusts their behavior enough in such a way that the seller shares in this loss in surplus. In other words, for the seller, the gains from more rapid inferences are outweighed by the losses from the resulting information withholding by the buyer.

Note that the range of values of t is different for Figures 9 and 10. Since we have normalized the value of m to lie between 0 and 1, fixed ranges of t are unduly restrictive, since they result in some t values that are significantly higher or lower than the values of v. In the subsequent analysis, as alluded to earlier, we take this further by investigate ranges of t that are between 20% and 100% of values of v.

Figure 11 illustrates the reductions in optimal customization levels as k increases, highlighting the differential effect these changes have on low and high valuation buyers. The figure illustrates that as m decreases as k increases, higher valuation buyers choose increasingly lower levels of customization. Also indicated is that this effect is independent of the relative values of v and t – in other words, for the same value of t as a percentage of v, a higher valuation buyer still chooses a lower level of customization.

[INSERT FIGURE 11 HERE]

In addition, Figure 11 highlights another interesting point – that improving agent technology has a much higher marginal effect on lower valuation buyers than on higher valuation buyers. The intuition behind this is that the effect of improved inference rates has a much higher net effect on buyers choosing higher values of m than on those choosing lower values of customization (the net reduction in m required to maintain the same value of θ is higher at higher values of m), and, consequently, the low valuation buyers, who choose higher values of m, are more adversely affected.

It is clear from the results thus far that increases in k reduce both buyer surplus and seller revenues, and that the driver of this is reductions in total surplus caused by effectively lower levels of customization chosen. A related issue of interest is how the *split* in total surplus is affected by changes in the rate of inference. In other words, while the size of the total surplus pie decreases as k increases, does an increase in k cause the seller to get a larger slice of this smaller pie?

[INSERT FIGURE 12 AND 13 HERE]

Some results from this portion of our analysis of this point are illustrated in Figures 12 and 13. It is clear from the figures that, as buyer valuations increase, sellers universally attract increasingly larger portions of the total surplus, across different values of k. This is illustrated by the fact that as v increases, the seller percentage revenue curves of Figure 12 move up, while the buyer percentage surplus curves of figure 13 move down. This result drives mixed outcomes in terms of total surplus splits – for low valuation buyers, it appears that sellers do indeed extract higher percentages of the total surplus, as the inference rates of their agents increases. However, for higher valuation buyers, the opposite is true.

5 Managerial Insights and Ongoing Work

In the context of the questions we address, economists have traditionally examined issues relating to price discrimination (Layson, 1994, Schmalensee,1981) and horizontal and vertical product differentiation (Chamberlain,1953, Lancaster, 1975) as independent problems. Information systems research, on the other hand, has focused on how to build systems that learn more efficiently from consumer information. Our paper enhances both streams of research, by examining price discrimination in the context of the information gained from product differentiation, and indicating that more efficient learning is not always better.

We observe a number of web-based markets consistent with our modeling framework – in which costless and potentially perfect customization are prevalent, and in which buyers reveal information about their possible price preferences through their product choices. Information products are easy to customize (in that the customization costs to the seller are negligible, and there are no significant transactions costs, such as manufacturing delay and logistical complexities associated with such customization). Many retailers of information products on the net such as the Wall Street Journal, Business Week and Yahoo allow users (buyers) to customize what they wish to see when they visit these sites. The ability to provide customization in news and information products is usually dependent on the extent to which the seller can make accurate references based on consumer preferences.

Differential pricing is also not uncommon. Many of these web portals (like Yahoo, Lycos, Infoseek and Excite) use this information to place targeted advertisements at buyers who are more likely to buy these items. Targeted advertisements cost anything from 100% to 250% higher than bulk advertisements on these customizable portals (Varian, 1999, 33). Some electronic stock trading sites observe buyer preferences and offer them differential rates for stock quotes which are based on the extent to which stock quotes are delayed. If an investor is considered "impatient" she is offered a package whereby she pays $50 for portfolio analysis based on real time stock quotes as opposed to an investor who may be seen by the web site owner as having a relatively lower value for her time and who is therefore offered a package priced at $8.95 for portfolio analysis based on stock quotes that are 20 minutes old. While these are not examples of agent-based differential pricing, they indicate that Web-based firms are beginning to use preference information to price and customize dynamically.

Another example is that of the market for current news. This is essentially a market where the product should resemble a commodity. Yet Reuters controls 68% of this market, and enjoys near-monopoly pricing power for its services, since it allows users to customize its new services to a degree that is not matched by its competitors (Varian, 1999).

Two key insights from our analysis, that apply to such markets as they evolve towards one-on-one dynamic pricing, are the following:

- Intelligent agents cause buyers on the higher end of the market to move away from customizing their product choices, despite the fact that they actually value these ideally customized products more than lower-end buyers. This result hold not only for fixed values of their costs of commoditization, but also for fixed fractions of buyer utility from customization.
- As these buyers adjust their optimal product choices in response to better demand agent technologies, sellers may experience diminishing revenues, since the gains from better buyer valuation information are countered by the lowering of the total surplus that the seller eventually extracts a portion of.

One implication of these results is that sellers may actually benefit from limiting their use of buyer preference information to infer willingness-to-pay, so long as they credibly inform their customers that they are doing so. While this may seem like an odd prescription, this kind of behavior is already widely observed in the context of consumer privacy. In Section 1, we had discussed the focus of trade-press attention on the issue of personal privacy, heightened recently by the RealAudio and DoubleClick cases. Clearly, on the face of it, companies could benefit by using their customers' personal information as much as possible. However, a number of them willingly choose to assure their customers that they will not use or sell this information, and they make these statements credible through the endorsement of organizations like TRUSTe and BBB Online (the online division of the Better Business Bureau).

It is likely that this choice by Web companies is driven not by a genuine desire to protect their customers' privacy, but because potential customers may shy away from sites that use their *personal information*. In other words, unless a company promises not to use the information much, they won't get the information at all. Our analysis shows that sellers using intelligent demand agents will face exactly the same trade-off, and it is likely that a similar structure will evolve, where sellers credibly promise not to extract too much of the information rents they get from their buyer's preference descriptions. It is possible that technological watchdog agencies analogous to TRUSTe may emerge as demand agents become more popular. It is also likely that multiple sellers will seek the services of a single, well-known intelligent agent technology, which buyers understand and trust. The industrial organization implications of this are interesting, since it indicates immense market potential for a company that can establish itself as the trusted agent intermediary.

The differential impact that intelligent agents have on high and low valuation buyers has interesting implications as well. Figures 14 and 15 illustrate the nature of the sources of revenue and surplus in markets driven by intelligent agents. Contrasting the two figures, an immediate implication is that the desirability of these agents is higher in markets where the average cost of commoditization is lower. In other words, in a market where customers are more product quality sensitive, using a pricing agent has a potentially adverse effect on seller revenues. On the other hand, seller revenues may increase vis-a-vis fixed pricing, if buyers in the market are not very sensitive to customization.

[INSERT FIGURE 14 AND 15 HERE]

An important observation is that higher valuation buyers are more adversely affected by demand agents. Figures 14 and 15 clearly illustrate how the 'deadweight loss' – the lost value that could have been tapped through transactions – shifts from the low end of the market to the high end of the market. This indicates that intelligent agents could cause some 'equalizing' of consumer surplus, as alluded to in Section 4. When a seller uses a demand agent, while the magnitude of total consumer surplus often is reduced, the distribution of surplus is far more even between buyers of varying valuation, which is illustrated by a comparison of the agent-driven surplus distributions to those with a fixed price[8].

Social equity aside, from the sellers point of view, the high-end buyers are the ones who actually have higher intrinsic profit potential for the seller, and if agent technologies affect them more adversely, this could be of concern to merchants. One strategy for sellers in this context is to credibly commit to using the inferencing mechanism of the agent on only lower valuation buyers, and one way of doing this is by committing to a fixed maximum price. This way, buyers on the low-end of the market, who may actually have been shut out with a fixed price, can enter the market. Simultaneously, buyers with high valuations can choose their ideal product with the assurance that even if the demand agent infers their true valuation, they are protected with the guarantee of a maximum price.

This kind of system is analogous to the observed sales strategy adopted by merchants who use online auctions – another kind of valuation revelation mechanism. Typically, auction houses (and their supplying manufacturers) like OnSale auction products that are targeted at low-end buyers –

[8] These comparisons are qualitative. A precise comparison requires us to assume an upper bound on consumer valuations, which changes the behavior of a demand agent close to this bound.

second hand and refurbished products. Interestingly, OnSale sells new, high-end products as well, but does so at a fixed price. This strategy separates the market in the manner we described (with the maximum price being the fixed price), and we anticipate similar market segmentation strategies from Web merchants who adopt intelligent agent technologies.

This paper is the first systematic analysis of the business implications of intelligent agent technologies. We are currently enhancing this research to incorporate a systematic economic model of inferencing across customers. We are also analyzing a model with two competing firms, in an effort to understand how competition affects the choice of technology. Preliminary results indicate that while less efficient technology could be a symmetric optimal equilibrium choice, competitors may also split the market, with the more technologically able company targeting the lower end of the market. Our current results have allowed us to comment on the economic implications of technologies that infer buyer valuations in a market for customized products. They are consistent with contemporary business trends, and prescribe business strategies for the many companies who will be faced with the decision of whether to use agent technology, and if so, how best to design and target it. Our hope is that our paper will serve as the starting point for research that further enhances understanding of the exciting new agent-driven world of business.

6 References

1. Anderson, C., 1997. In Search of the Perfect Market. *The Economist* **343** (8016) E3-E5.

2. Andrews, W. 1999. Buyers' guides look to sell data on consumers' wants: aim is to let sellers see exactly what buyers are seeking. Internet World (Jan. 18).

3. Anonymous.1999. Business: Direct Hit. *The Economist* **350** (8101) 55-57.

4. Arunkundram, R. and Sundararajan, A. 1998. An Economic Analysis of Electronic Secondary Markets: Installed Base, Durability, Technology and Firm Profitability. *Decision Support Systems* **24** (1), 3-16

5. Bakos, J.Y. 1991. A Strategic Analysis of Electronic Marketplaces. *MIS Quarterly* **15** (3), 295-311.

6. Bakos, J.Y. 1997. Reducing Buyer Search Costs: Implications for Electronic Marketplaces. *Management Science* **43**(12), 1676 -1693.

7. Bakos, J. Y. and Brynjolfsson, E. 1999. Bundling Information Goods: Pricing, Profits and Efficiency. *Management Science* (forthcoming).

8. Balabanovic, M. and Shoham, Y. 1997. Fab: Content-based, Collaborative Recommendation. *Communications of the ACM* **40** (3), 66-72.

9. Banker, R., Khosla, I. and Sinha, K. 1998. Quality and Competition. *Management Science* 44 (9), 1179-1192.

10. Barua, A., Pinnell, J., Shutter, J. and A.B. Whinston. 1999. Measuring the Internet Economy. Working Paper, Center for Research in Electronic Commerce, University of Texas, Austin.

11. Bayers, C. 2000. Capitalist EConstruction. *Wired Magazine* (March), 214-222.

12. Brynjolfsson, E., and Smith, M., Frictionless Commerce? A Comparison of Internet and Conventional Retailers, Working Paper, MIT Sloan School of Management.

13. Bui, T. and Lee, J. 1999. An Agent-Based Framework for Building Decision Support Systems. *Decision Support Systems* **25** (3), 225-237.

14. Chamberlin, E.H. 1953. The Product as an Economic Variable. *The Quarterly Journal of Economics* **67** (1) 1-29.

15. Clemons, E. K., Hann, I., and Hitt, L. 1999. The Nature of Competition in Electronic Markets: An Empirical Investigation of Online Travel Agent Offerings. Working Paper, The Wharton School, University of Pennsylvania.

16. Dhar, V. and Sundararajan, A. 1999. Customer Interaction Patterns in Electronic Commerce: Maximizing Information Liquidity for Adaptive Decision Making. Working Paper IS-99-017, Center for Information Intensive Organizations, New York University.

17. Dutta, S. and Segev, A. 1999. Business Transformation on the Internet. Working Paper WP-1035, Fisher Center for Information Technology, University of California, Berkeley.

18. Fingar, P. 1999. Intelligent Agents: The Key to Open eCommerce Building The Next-Generation Enterprise. http://home1.gte.net/pfingar/csAPR99.html

19. Frey, L., and Fisher, D. 1999. Modeling Decision Tree Performance with the Power Law. In *Proceedings of the Seventh International Workshop on Artificial Intelligence and Statistics.*

20. Hof, R.D. 1998. Now It's Your Web: The Net is Moving Toward One-to-One Marketing–and That Will Change How All Companies Do Business. *Business Week.*

21. Johnson , C. R. 1997. Intelligent agents breathe life into Internet. http://www.eet.com/news/97/946news/

22. Kambil, A. and van Heck, E. 1998. Re-engineering the Dutch Flower Auctions: A Framework for Analyzing Exchange Organizations. *Information Systems Research 9 (1), 1-19.*

23. Kautz, H., Selman, B., and Shah, M. 1997. Referral Web: Combining Social Networks and Collaborative Filtering. *Communications of the ACM* **40**(3), 63-65.

24. Kraut, R. , Mukhopadhyay, T., Szczypula, J., Kiesler, S. and Scherlis, B. Information and Communication: Alternative Uses of the Internet in Households. *Information Systems Research* ***10*** *(4), 287-303.*

25. Lancaster, K.J. 1975. Socially Optimal Product Differentiation. *American Economic Review* **65** (4), 567-585.

26. Layson, S.K. 1994. Market Opening Under Third-Degree Price Discrimination. *Journal of Industrial Economics* **42** (3), 335-340.

27. Maes, P. 1994. Agents that Reduce Work and Information Overload. *Communications of the ACM* **37**(7), 31-40.

28. Malone, T.W., Yates, J., and Benjamin, R.I. 1987. Electronic Markets and Electronic Hierarchies: Effects of Information Technology on Market Structure and Corporate Strategies. *Communications of the ACM* **30**(6) 484-497.

29. Mendelson, H. and Jones, R. 1998. Product and Price Competition for Information Goods. Working Paper, University of Rochester.

30. Millman, H. 1998. Agents at Your Service: The Expansive Sea of Online Data Calls Out for an Intelligent Solution. *InfoWorld* **20** (7) (February 16th).

31. Provost, F., Jensen, D. and Oates, T. 1999. Efficient Progressive Sampling.

32. Salop, S.C. 1979. Monopolistic Competition with Outside Goods. *The Rand Journal of Economics* **10**(1), 141-156.

33. Schmalensee, R.1981. Output and Welfare Implications of Monopolistic Third-Degree Price Discrimination. *American Economic Review* **71**(1), 242-247.

34. Singh, Z. 1999. Super Markets (New Rules). *Business 2.0* (March).

35. Stigler, G.J. 1961. The Economics of Information. *The Journal of Political Economy* **69**(3), 213-225.

36. Stohr, E.A., and Viswanathan, S. 1999. Recommendation Systems: Decision Support for the Information Economy. In K.E.Kendall, ed. *Emerging Information Technologies*, Sage Publications, CA. 21-44.

37. Vakrat, Y. and Seidmann, A. 1999. Can Online Auctions Beat Online Catalogs In *Proceedings of the Twentieth International Conference on Information Systems.*

38. Varian, H.R. 1999. *Information Rules.* Harvard Business School Press, 1999.

39. Weber, B. 1998. Elements of Market Structure for Online Commerce. In Kemerer, C. K. (ed.), *Information Technology and Industrial Competitiveness: How I.T. Shapes Competition.* Kluwer Academic Publishers.

40. Weise, E. 1997. Turning the Net into Your Personal Shopping Valet. *USA Today.* Nov. 25 04D.

41. Yankee Group, 2000. Online Retailing: The Growth of Dynamic Pricing. *Yankee Group Report, Internet Market Strategies*, Vol. 6, No. 3 (March).

A Appendix: Proofs

A.1 Proof of Lemma 1

Suppose the seller were to set a price x. If the buyer's net valuation $v - \tau(\theta)$ is greater than or equal to x, then the sale will be successful, at the price of x. If, on the other hand, $v - \tau(\theta) < x$, no sale will be made. Since the seller's prior is that v is uniform in $[\varepsilon, \varepsilon + \theta]$, the seller will set a price x such that $x + \tau(\theta) \in [\varepsilon, \varepsilon + \theta]$. At this price x:

$$\Pr[v - \tau(\theta) \geq x] = \Pr[v \geq x + \tau(\theta)] = (\frac{\varepsilon + \theta - x - \tau(\theta)}{\theta}),$$

so long as $x + \tau(\theta) \geq \varepsilon$. Therefore, the seller's expected profits are:

$$\pi(x, \varepsilon, \theta) = \frac{x(\varepsilon + \theta - x - \tau(\theta))}{\theta}.$$

The seller maximizes expected revenue. First order conditions yield:

$$x^* = \frac{\varepsilon + \theta - \tau(\theta)}{2}.$$

x^* is the unique solution, so long as $x^* + \tau(\theta) \in [\varepsilon, \varepsilon + \theta]$. If, on the other hand, $x^* + \tau(\theta)$ lies outside the interval, then the optimal price will be set at the lower bound of the buyer's estimated valuation, or at a price x such that $x + \tau(\theta) = \varepsilon$, or $x = \varepsilon - \tau(\theta)$. This occurs when:

$$\frac{\varepsilon + \theta - \tau(\theta)}{2} + \tau(\theta) \leq \varepsilon,$$

or when $\varepsilon \geq \theta + \tau(\theta)$.

Therefore, optimal price p^* is given by:

$$p^* = \frac{\varepsilon + \theta - \tau(\theta)}{2} \text{ if } \varepsilon \leq \theta + \tau(\theta)$$
$$p^* = \varepsilon - \tau(\theta) \text{ if } \varepsilon \geq \theta + \tau(\theta),$$

which completes the proof.

A.2 Proof of Proposition 2

(a) $\theta \leq \frac{v-\tau(\theta)}{2}$.

$\theta \leq \frac{v-\tau(\theta)}{2}$ implies that $v - \theta \geq \theta + \tau(\theta)$. This implies that $v - \theta > \tau(\theta)$, and hence, the buyer's prior is that ε is uniform in $[v - \theta, v]$.

Since $\varepsilon \geq v - \theta$, this also implies that $\varepsilon \geq \theta + \tau(\theta)$. According to Lemma 1, the revenue maximizing price in this range of values of ε is $p^* = \varepsilon - \tau(\theta)$. The lower support for ε is $v - \theta$, and the upper support is v. Therefore, the price $p(\theta)$ that the buyer expects is distributed in $[v - \theta - \tau(\theta), v - \tau(\theta)]$, $f(p) = \frac{1}{\theta}$ in this interval, and $f(p)$ is zero everywhere else.

(b) $\frac{v-\tau(\theta)}{2} \leq \theta \leq v - \tau(\theta)$.

$\theta \leq v - \tau(\theta)$ implies that $v - \theta \geq \tau(\theta)$, and hence, the buyer's prior is that ε is uniform in $[v - \theta, v]$.

However $\frac{v-\tau(\theta)}{2} \leq \theta \leq v - \tau(\theta)$ implies that $v - \theta \leq \theta + \tau(\theta) \leq v$. Therefore, $\varepsilon \leq \theta + \tau(\theta)$ when $\varepsilon \in [v - \theta, \theta + \tau(\theta)]$, and $\varepsilon \geq \theta + \tau(\theta)$ when $\varepsilon \in [\theta + \tau(\theta), v]$. According to Lemma 1, these two intervals induce two different prices based on the values of θ and ε. Substituting the intervals $[v - \theta, \theta + \tau(\theta)]$ and $[\theta + \tau(\theta), v]$ into the corresponding prices functions specified by Lemma 1 yields the result.

(c) $\theta \geq v - \tau(\theta)$ implies that $\tau(\theta) \geq v - \theta$, and hence, the buyer's prior is that ε is uniformly distributed in $[\tau(\theta), v]$.

Also, $\theta \geq v - \tau(\theta)$ implies that $v \leq \theta + \tau(\theta)$. Therefore, $\varepsilon \leq \theta + \tau(\theta)$, since $\varepsilon \leq v$. From Lemma 1, it follows that the seller's revenue maximizing price $p = \dfrac{\varepsilon + \theta - \tau(\theta)}{2}$. Given the buyer's prior on ε, the price $p(\theta)$ that the buyer expects is uniformly distributed in $[\dfrac{\tau(\theta) + \theta - \tau(\theta)}{2}, \dfrac{v + \theta - \tau(\theta)}{2}]$, or in $[\dfrac{\theta}{2}, \dfrac{v + \theta - \tau(\theta)}{2}]$, with $f(p) = \dfrac{2}{v - \tau(\theta)}$ in this interval, and $f(p) = 0$ everywhere else.

A.3 Proof of Lemma 3

(a) If $\theta \leq \dfrac{v - \tau(\theta)}{2}$, then, by Proposition 2(a), that $p(\theta)$ is uniformly distributed in $[v - \tau(\theta) - \theta, v - \tau(\theta)]$. The highest price that the buyer expects is therefore $v - \tau(\theta)$, which is low enough to give the buyer non-negative surplus. Hence, the buyer always buys when $\theta \leq \frac{v-\tau(\theta)}{2}$

The buyer's expected surplus is therefore:

$$\begin{aligned}
\psi(\theta) &= \int_{v-\tau(\theta)-\theta}^{v-\tau(\theta)} [v-\tau(\theta)-p(\theta)]f(p)dp \\
&= \frac{1}{\theta}\int_{v-\tau(\theta)-\theta}^{v-\tau(\theta)} [v-\tau(\theta)-p(\theta)]dp \\
&= v-\tau(\theta)-\frac{1}{\theta}\left[\frac{(v-\tau(\theta))^2-(v-\tau(\theta)-\theta)^2}{2}\right]=\frac{\theta}{2}.
\end{aligned}$$

(b) If $\frac{v-\tau(\theta)}{2} \leq \theta \leq v-\tau(\theta)$, then we know from Proposition 1 that:

$$\begin{aligned}
f(p) &= \frac{2}{\theta} \text{ for } p(\theta) \in \left[v-\frac{\tau(\theta)}{2}, \theta\right] \text{ and} \\
f(p) &= \frac{1}{\theta} \text{ for } p(\theta) \in [\theta, v-\tau(\theta)]
\end{aligned}$$

The highest price that the buyer expects is therefore $v-\tau(\theta)$ – this price is low enough to give the buyer non-negative surplus. Hence, the buyer always buys when $\frac{v-\tau(\theta)}{2} \leq \theta \leq v-\tau(\theta)$.

Given the buyer's prior on $p(\theta)$, the buyer's expected surplus is therefore:

$$\begin{aligned}
\psi(\theta) &= \int_{v-\frac{\tau(\theta)}{2}}^{v-\tau(\theta)} [v-\tau(\theta)-p(\theta)]f(p)dp \\
&= \left(\frac{2}{\theta}\int_{v-\frac{\tau(\theta)}{2}}^{\theta} [v-\tau(\theta)-p(\theta)]dp\right)+\left(\frac{1}{\theta}\int_{\theta}^{v-\tau(\theta)} [v-\tau(\theta)-p(\theta)]dp\right) \\
&= v-\tau(\theta)-\frac{\theta}{2}-\frac{v^2-2v\tau(\theta)+[\tau(\theta)]^2}{4\theta}
\end{aligned}$$

(c) and (d) If $\theta \geq v-\tau(\theta)$, by Proposition 1, $p(\theta)$ is uniformly distributed in $[\frac{\theta}{2}, \frac{v+\theta-\tau(\theta)}{2}]$, and $f(p) = \frac{2}{v-\tau(\theta)}$ in this interval. However, $\theta \geq v-\tau(\theta)$ implies that $\frac{\theta+v-\tau(\theta)}{2} \geq \frac{v-\tau(\theta)+v-\tau(\theta)}{2}$, or that $\frac{v+\theta-\tau(\theta)}{2} \geq v-\tau(\theta)$. Therefore, there is always a set of prices in $[\frac{\theta}{2}, \frac{v+\theta-\tau(\theta)}{2}]$ for which the buyer would get a non-positive surplus from buying.

To establish that the buyer gets non-negative surplus at some price in $[\frac{\theta}{2}, \frac{v+\theta-\tau(\theta)}{2}]$, it is necessary that the lowest possible price, $\frac{\theta}{2}$, is lower than $v-\tau(\theta)$, i.e. that $\frac{\theta}{2} \leq v-\tau(\theta)$, or $\theta \leq 2[v-\tau(\theta)]$. This proves part (d), since $\theta \geq 2[v-\tau(\theta)]$ implies that the buyer does not buy (and therefore gets zero surplus) for all of the prices in $[\frac{\theta}{2}, \frac{v+\theta-\tau(\theta)}{2}]$.

Now consider the case where $v-\tau(\theta) \leq \theta \leq 2[v-\tau(\theta)]$. This implies that $\frac{\theta}{2} \leq v-\tau(\theta) \leq \frac{v+\theta-\tau(\theta)}{2}$. The buyer gets a non-negative surplus for $p \in [\frac{\theta}{2}, v-\tau(\theta)]$, and does not buy if

$p \geq v - \tau(\theta)$. The buyer's expected surplus is therefore:

$$\begin{aligned}
\psi(\theta) &= \int_{\theta/2}^{v-\tau(\theta)} [v - \tau(\theta) - p] f(p) dp + \int_{v-\tau(\theta)}^{\frac{v+\theta-\tau(\theta)}{2}} 0.f(p)dp \\
&= \frac{2}{v-\tau(\theta)} \int_{\theta/2}^{v-\tau(\theta)} [v - \tau(\theta) - p] dp \\
&= 2[v - \tau(\theta) - \frac{\theta}{2}] - \frac{2}{v-\tau(\theta)} \left(\frac{[v-\tau(\theta)]^2 - \frac{\theta^2}{4}}{2} \right) \\
&= \frac{(2[v-\tau(\theta)] - \theta)^2}{4[v-\tau(\theta)]}.
\end{aligned}$$

This completes the proof.

A.4 Proof of Proposition 4

In order to simplify exposition, we defined the following values of θ :

(i) θ_1 satisfies $\theta_1 = \frac{v-\tau(\theta_1)}{2}$;

(ii) θ_2 satisfies $\theta_2 = v - \tau(\theta_2)$

(iii) θ_3 satisfied $\theta_3 = 2[v - \tau(\theta_3)]$

We first establish that if $\tau'(\theta) > 0$, then $\theta_1 < \theta_2 < \theta_3$, for values of θ that satisfy $\tau(\theta) < v$. This is the range of θ values that are of interest.

If $\tau'(\theta) > 0$, then $\theta + \tau(\theta)$ is strictly increasing[9] in θ. Since $2\theta_1 = v - \tau(\theta_1)$, we get $\tau(\theta_1) + \theta_1 = v - \theta_1$. Also, $\tau(\theta_2) + \theta_2 = v$, which implies that $\tau(\theta_2) + \theta_2 > \tau(\theta_1) + \theta_1$, which implies that $\theta_2 > \theta_1$.

Now, assume that $\theta_3 \leq \theta_2$. This implies that $\tau(\theta_3) + \theta_3 \leq \tau(\theta_2) + \theta_2$, which implies that $\tau(\theta_3) + \theta_3 \leq v$, or $\theta_3 \leq v - \tau(\theta_3)$. However, since we are considering values of θ such that $v > \tau(\theta)$, this contradicts $\theta_3 = 2[v - \tau(\theta_3)]$.

Having established this, we can now characterize the buyer's surplus function as:

$$\begin{aligned}
\psi(\theta) &= \psi_1(\theta) = \frac{\theta}{2} \text{ for } \theta_{\min} \leq \theta \leq \theta_1; \\
\psi(\theta) &= \psi_2(\theta) = v - \tau(\theta) - \frac{\theta}{2} - \frac{[v-\tau(\theta)]^2}{4\theta} \text{ for } \theta_1 \leq \theta \leq \theta_2; \\
\psi(\theta) &= \psi_3(\theta) = \frac{(2[v-\tau(\theta)] - \theta)^2}{4[v-\tau(\theta)]} \text{ for } \theta_2 \leq \theta \leq \theta_3, \text{ and} \\
\psi(\theta) &= 0 \text{ for } \theta \geq \theta_3.
\end{aligned}$$

(a) If $\theta_1 \geq \theta_{\max}$, then the range of feasible values of θ are such that $\psi(\theta) = \psi_1(\theta)$ for all θ. Since $\psi_1(\theta)$ is strictly increasing, the buyer chooses the highest possible value of θ, which is $\theta_{\max}$.

[9] Actually, all we need here is that $\tau'(\theta) \geq 0$; however, we need τ to be strictly increasing later in the proof. Since $m(\theta)$ is strictly decreasing, $\tau(\theta)$ is strictly increasing, anyway.

(b) In the interval $\theta_{\min} \leq \theta \leq \theta_1$, ψ_1 is strictly increasing, and hence the value of θ that maximizes $\psi(\theta)$ in this interval is $\theta = \theta_1$.

Now, consider the interval $\theta_2 \leq \theta \leq \theta_3$. The first derivative of the surplus function ψ in this interval is:

$$\begin{aligned}\psi'(\theta) &= \psi_3'(\theta) = \frac{d}{d\theta}\frac{(2[v-\tau(\theta)]-\theta)^2}{4[v-\tau(\theta)]} \\ &= -\frac{(2[v-\tau(\theta)]-\theta)(2v-2\tau(\theta)+\tau'(\theta)[\theta+2v-2\tau(\theta)]}{4[v-\tau(\theta)]^2}.\end{aligned}$$

Now, in this interval, $\theta \leq 2[v-\tau(\theta)]$. Also, since $\tau'(\theta) > 0$, and since the buyer will only make choices of θ such that $v \geq \tau(\theta)$, we have:

$$2[v-\tau(\theta)]-\theta \geq 0;$$

$$2v-2\tau(\theta) \geq 0;$$

$$\tau'(\theta)[\theta+2v-2\tau(\theta)] > 0.$$

This implies that $\psi'(\theta) < 0$ in the interval $\theta_2 \leq \theta \leq \theta_3$, or that $\psi(\theta_2) > \psi(\theta)$ for all θ in $[\theta_2, \theta_3]$. Finally, $\psi(\theta) = 0$ for $\theta \geq \theta_3$, so this is not an interval of interest to the buyer.

Therefore, the optimal value of θ for the buyer to induce lies in $[\theta_1, \theta_2]$. This establishes that the buyer's optimal choice is the solution to the maximization problem specified in the proposition.

$\psi_2'(\theta) = 0$ is the first order necessary condition for this optimization problem. In order to prove that it is sufficient, we require two conditions – that ψ_2 is concave in the relevant interval[10], and that this first order condition holds for at least one point in (θ_1, θ_2).

To establish concavity, we calculate the second derivative of $\psi_2(\theta)$:

$$\psi_2''(\theta) = \frac{-(v-\tau(\theta)+\theta\tau'(\theta))^2 - \theta(2\theta-v-\tau(\theta))\tau''(\theta)}{2\theta^3}.$$

Since the first term $-(v-\tau(\theta)+\theta\tau'(\theta))^2$ in the numerator is always negative, the entire expression is negative if $\theta(2\theta-v-\tau(\theta))\tau''(\theta) \geq 0$. However, $\theta \geq 0$ and $2\theta - v - \tau(\theta) \geq 0$ in the interval (θ_1, θ_2). Hence, $\tau''(\theta) \geq 0$ ensures that $\psi_2''(\theta) < 0$.

Also note that the first derivative of $\psi_2(\theta)$ is:

$$\psi_2'(\theta) = \frac{(v-\tau(\theta))^2}{4\theta^2} + \frac{2\tau'(\theta)(v-\tau(\theta))}{\theta} - \tau'(\theta) - \frac{1}{2}.$$

Since $2\theta_1 = v - \tau(\theta_1)$, we get:

$$\psi_2'(\theta_1) = \frac{(v-\tau(\theta_1))^2}{4\theta_1^2} + \frac{\tau'(\theta_1)(v-\tau(\theta_1))}{2\theta_1} - \tau'(\theta_1) - \frac{1}{2}$$

[10] Actually, we could do with weaker conditions – all that is required here is that $\psi''(\theta) < 0$ when $\psi'(\theta) = 0$, or that ψ is quasiconcave. We found that ψ is quasiconcave under a number of conditions, but it is not clear that it is always so. Furthermore, establishing quasiconcavity would add little to our intuition about buyer behavior with an intelligent agent, and so we did not pursue the mathematics of this further.

$$
\begin{aligned}
&= \frac{(2\theta_1)^2}{4\theta_1^2} + \frac{\tau'(\theta_1)(2\theta_1)}{2\theta_1} - \tau'(\theta_1) - \frac{1}{2} \\
&= \frac{1}{2} > 0.
\end{aligned}
$$

Also, since $\theta_2 = v - \tau(\theta_2)$, we get:

$$
\begin{aligned}
\psi_2'(\theta_2) &= \frac{(v-\tau(\theta_2))^2}{4\theta_2^2} + \frac{\tau'(\theta_2)(v-\tau(\theta_2))}{2\theta_2} - \tau'(\theta_2) - \frac{1}{2} \\
&= \frac{(\theta_2)^2}{4\theta_1^2} + \frac{\tau'(\theta_2)(\theta_2)}{2\theta_1} - \tau'(\theta_2) - \frac{1}{2} \\
&= -\frac{1}{2} - \frac{\tau'(\theta_2)}{2} < 0,
\end{aligned}
$$

since $\tau(\theta)$ is increasing.

Therefore, the function $\psi_2'(\theta)$ is strictly positive at θ_1 and strictly negative at θ_2. By continuity, it must be zero at least one point in (θ_1, θ_2). This completes the proof.

A.5 Proof of Proposition 5

Proposition 4 establishes that the buyer's optimal choice of θ will always be such that $\theta < \theta_2$. Therefore, the buyer always buys from the seller, irrespective of the actual window $[\varepsilon, \varepsilon + \theta^*]$ that the intelligent agent provides the seller. Therefore, the seller's expected revenues are simply the expected value of the price she will charged, calculated over the distribution of ε.

(a) If $\theta_{\max} > \frac{v-\tau(\theta_{\max})}{2}$, then the buyer's optimal θ^* lies in (θ_1, θ_2). Hence, the price set by the seller could be either $\frac{\varepsilon+\theta-\tau(\theta)}{2}$ or $\varepsilon - \tau(\theta)$, depending on whether ε is greater than or less than $\theta^* + \tau(\theta^*)$. Consequently, the expected revenues of the seller are:

$$
\begin{aligned}
\pi(\theta^*|v) &= \frac{1}{\theta^*}\left(\int_{v-\theta^*}^{\theta^*+\tau(\theta^*)} \frac{\varepsilon + \theta^* - \tau(\theta^*)}{2} d\varepsilon + \int_{\theta^*+\tau(\theta^*)}^{v} [\varepsilon - \tau(\theta^*)] d\varepsilon \right) \\
&= \frac{\theta^*}{2} + \frac{(v-\tau(\theta^*))^2}{4\theta^*}.
\end{aligned}
$$

(b) $\theta_{\max} \leq \frac{v-\tau(\theta_{\max})}{2}$, then the buyer's optimal $\theta^* \leq \frac{v+\tau(\theta^*)}{2}$, which means that the window returned by the intelligent agent will be such that $\varepsilon \leq \theta^* + \tau(\theta^*)$. The expected revenues of the seller are therefore:

$$
\begin{aligned}
\pi(\theta^*|v) &= \frac{1}{\theta^*}\left(\int_{v-\theta^*}^{v} \frac{\varepsilon + \theta^* - \tau(\theta^*)}{2} d\varepsilon \right) \\
&= \frac{2v + \theta^* - 2\tau(\theta^*)}{4},
\end{aligned}
$$

which completes the proof.

A.6 Proof of Proposition 6

When $\theta(m) = (1-m)^2$, $\tau(\theta) = t\theta$. Therefore, $\tau(.)$ is (weakly) convex.

(a)Proposition 4 tells us that the value of θ that maximizes consumer surplus (when $\theta_{\max} \geq \frac{v-\tau(\theta_{\max})}{2}$) is the unique optimal choice θ^* of the seller solves $\psi_2'(\theta^*) = 0$. From Lemma 3, $\psi_2(\theta^*) = v - \tau(\theta) - \frac{\theta}{2} - \frac{[v-\tau(\theta)]^2}{4\theta}$. Substituting for $\tau(\theta)$, and equating $\frac{\partial(\psi_2(\theta^*))}{\partial\theta}$ to 0 yields:

$$\theta^* = \frac{v}{\sqrt{2+4t+t^2}}.$$

(b) Substitute $\theta^* = \frac{v}{\sqrt{2+4t+t^2}}$, in the expression for consumer surplus $\psi_2(\theta^*)$. The resulting expression is:

$$\psi_2(\theta^*) = \frac{\left(2+t-\sqrt{2+t\,(4+t)}\right)\,v}{2}.$$

The result follows.

(c) Proposition 5 specifies the expression for seller revenues. Substituting the value of $\theta^* = \frac{v}{\sqrt{2+4t+t^2}}$ into this expression:

$$\begin{aligned}\pi(\theta) &= \frac{\theta^*}{2} + \frac{(v-\tau(\theta^*))^2}{4\theta^*}.\\ \therefore\quad \pi^*(v,t) &= \pi\left(\frac{v}{\sqrt{2+4t+t^2}}\right) = \frac{v\left[(2+t\,(2+t)) - t\sqrt{2+t\,(4+t)}\right]}{2\sqrt{2+t\,(4+t)}},\end{aligned}$$

which completes the proof.

A.7 Proof of Corollary 7

(a) From Proposition 6, we have $\psi^*(v,t) = \frac{\left(2+t-\sqrt{2+t\,(4+t)}\right)\,v}{2}$. Therefore,

$$\frac{\partial\left(\psi^*(v,t)\right)}{\partial v} = \frac{\left(2+t-\sqrt{2+t\,(4+t)}\right)}{2} \geq 0 \text{ since } 2+t > \sqrt{2+t\,(4+t)}\ \forall\, t.$$

Differentiating $\psi^*(v,t)$ with respect to t, we obtain:

$$\frac{\partial\left(\psi(v,t)\right)}{\partial t} = \frac{\left(1-\frac{2+t}{\sqrt{2+t\,(4+t)}}\right)\,v}{2}$$

Since $2+t > \sqrt{2+t\,(4+t)}$, it follows that $1-\frac{2+t}{\sqrt{2+t\,(4+t)}} < 0$ and therefore $\frac{\partial(\psi(\theta^*))}{\partial t} < 0$. The result follows.

(b) From Proposition 6, we also have:

$$\pi^*(v,t) = \frac{v\left[(2+t\,(2+t)) - t\sqrt{2+t\,(4+t)}\right]}{2\sqrt{2+t\,(4+t)}}.$$

Differentiating with respect to v, we get:

$$\frac{\partial\left(\pi^*\left(v,t\right)\right)}{\partial v}=\frac{\left[\left(2+t\ \left(2+t\right)\right)-t\ \sqrt{2+t\ \left(4+t\right)}\right]}{2\sqrt{2+t\ \left(4+t\right)}}$$

Since, $\left(2+t\ \left(2+t\right)\right)>t\ \sqrt{2+t\ \left(4+t\right)}$, it follows that $\frac{\partial(\pi(\theta^*))}{\partial v}>0$, and therefore, the seller's profits are increasing in v.

Differentiating $\pi^*\left(v,t\right)$ with respect to t we get:

$$\frac{\partial\left(\pi^*\left(v,t\right)\right)}{\partial t}=\frac{\left(-1+\frac{t\,(6+t\,(6+t))}{(2+t\,(4+t))^{\frac{3}{2}}}\right)\ v}{2}$$

The equation $-1+\frac{t\,(6+t\,(6+t))}{(2+t\,(4+t))^{\frac{3}{2}}}=0$ has 3 roots, two of which are complex conjugates (of each other). The third root is given by:

$$t=-\left(\frac{5}{3}\right)-\frac{\sqrt{\frac{28}{9}-\frac{4\,2^{\frac{1}{3}}}{3}}}{2}-\frac{\sqrt{\frac{56}{9}+\frac{4\,2^{\frac{1}{3}}}{3}+\frac{272}{27\sqrt{\frac{28}{9}-\frac{4\,2^{\frac{1}{3}}}{3}}}}}{2}$$

Since this is always negative, the function is either always greater than or less than zero for all values of t greater than its real root value. It can be shown easily by substituting $t=0$, that the function is always negative. Therefore, the expression $-1+\frac{t\,(6+t\,(6+t))}{(2+t\,(4+t))^{\frac{3}{2}}}\leq 0$ for all real values of t. It follows that $\frac{\partial(\pi(\theta^*))}{\partial t}\leq 0$, and therefore, the seller's profits are decreasing in t. This completes the proof.

B Appendix: More 'accurate' intelligent agent

In Section 2, we had considered the possibility that the buyer makes a choice of θ such that $\theta\geq v-\tau(\theta)$ – which would imply that $v-\theta\leq\tau(\theta)$), and that $\varepsilon\leq\tau(\theta)$. Here, we had assumed that the intelligent agent would choose a ε such that $\varepsilon\in[\tau(\theta),v]$, and that the interval would still have a width of θ. Proposition X has shown that, under this assumption, a choice of $\theta\geq v-\tau(\theta)$ is never made by the buyer. This is reassuring, since it eliminates the possibility that, at optimality, our final surplus and profit functions are dependent on this assumption.

However, it introduces a doubt – were a different assumption to be made in this case – namely, that in this case, the IA would choose an $\varepsilon\in[v-\theta,v]$, and narrow the estimate of the buyer's valuation to $[\tau(\theta),\varepsilon+\theta]$ if it turned out that $\varepsilon\leq\tau(\theta)$ – would the buyer's behavior be affected. The purpose of this Appendix is to prove that even under the alternate assumption, the buyer still never chooses $\theta\geq v-\tau(\theta)$.

Suppose the IA were to behave in this alternate fashion: If $\theta\geq v-\tau(\theta)$, choose an $\varepsilon\in[v-\theta,v]$. If $\varepsilon\geq\tau(\theta)$, then give the seller the interval $[\varepsilon,\varepsilon+\theta]$. If $\varepsilon<\tau(\theta)$, then use the knowledge that $v\geq\tau(\theta)$ to give the seller a narrower interval $[\tau(\theta),\varepsilon+\theta]$ of the buyer's valuation. We investigate the seller's optimal pricing, and the corresponding expected buyer surplus under this assumption.

If provided such an interval $[\tau(\theta), \varepsilon + \theta]$, the seller notices that the width of the interval is $\varepsilon + \theta - \tau(\theta) < \theta$. Therefore, the seller's prior is that v is uniform in $[\tau(\theta), \varepsilon + \theta]$ with density $\frac{1}{\varepsilon+\theta-\tau(\theta)} > \frac{1}{\theta}$. This can only occur, of course, if $\theta \geq v - \tau(\theta)$.

A rational seller sets a price $x + \tau(\theta) \in [\tau(\theta), \varepsilon + \theta]$, or $x \in [0, \varepsilon + \theta - \tau(\theta)]$. At this price x, the seller's expected revenue is:

$$\Pr[v - \tau(\theta) \geq x] = \Pr[v \geq x + \tau(\theta)] = (\frac{\varepsilon + \theta - x - \tau(\theta)}{\varepsilon + \theta - \tau(\theta)}),$$

since the width of the prior on v is now $\varepsilon + \theta - \tau(\theta)$. Hence, the seller's expected revenues at a price x are:

$$x(\frac{\varepsilon + \theta - x - \tau(\theta)}{\varepsilon + \theta - \tau(\theta)}) = x - \frac{x^2}{\varepsilon + \theta - \tau(\theta)}.$$

The first order conditions for maximization yield:

$$1 - \frac{2p^*}{\varepsilon + \theta - \tau(\theta)} = 0, \text{ or } p^* = \frac{\varepsilon + \theta - \tau(\theta)}{2}.$$

Clearly, this value of p^* is within the permissible range of $x \in [0, \varepsilon + \theta - \tau(\theta)]$.

Suppose, on the other hand, that $\varepsilon \geq \tau(\theta)$. The seller's prior on v here is that $v \in [\varepsilon - \theta, \varepsilon]$. Since $\theta \geq v - \tau(\theta)$, which implies that $v \leq \theta + \tau(\theta)$, even at a value $\varepsilon = v$, $\varepsilon \leq \theta + \tau(\theta)$, and so the seller's optimal price, by Lemma 1, is $p^* = \frac{\varepsilon+\theta-\tau(\theta)}{2}$.

Therefore, even though the buyer does not know whether ε is greater than or less than $\tau(\theta)$, the buyer expects the seller to set a price $\frac{\varepsilon+\theta-\tau(\theta)}{2}$, when given an interval with upper bound $\varepsilon + \theta$. The buyer's prior on ε here is that $\varepsilon \in [v - \theta, v]$. Hence, the buyer's expected price is uniformly distributed in $[\frac{v-\tau(\theta)}{2}, \frac{v+\theta-\tau(\theta)}{2}]$, with density $\frac{2}{\theta}$.

Since $\theta \geq v - \tau(\theta)$, $\frac{v-\tau(\theta)+\theta}{2} \geq \frac{v-\tau(\theta)+(v-\tau(\theta))}{2}$, or $\frac{v-\tau(\theta)+\theta}{2} \geq v - \tau(\theta)$. Hence, there are some expected prices in $[\frac{v-\tau(\theta)}{2}, \frac{v+\theta-\tau(\theta)}{2}]$ for which the buyer does not buy. The buyer's expected surplus is therefore:

$$\psi_4(\theta) = \frac{2}{\theta} \int_{\frac{v-\tau(\theta)}{2}}^{v-\tau(\theta)} (v - \tau(\theta) - p)dp = \frac{(v - \tau(\theta))^2}{4}.$$

It is easily shown that $\psi_4'(\theta) < 0$, and hence, in this interval, the buyer chooses the lowest possible θ, which is θ_2 from Proposition 4.

Therefore, even under this different assumption about the way the intelligent agent operates, the buyer's choice is still as specified by Proposition 4.

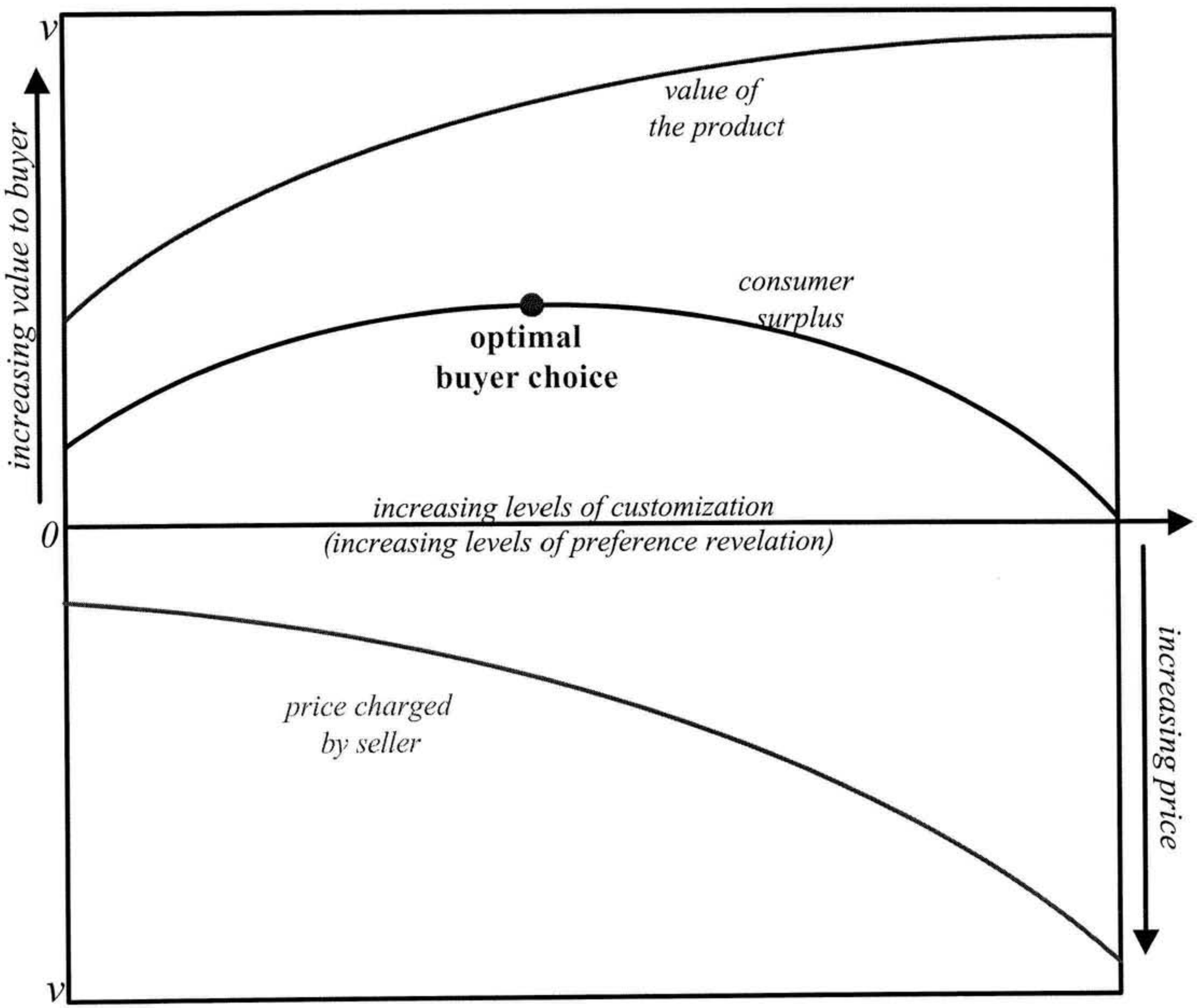


Figure 1: The buyer's fundamental trade-off, when facing a demand agent

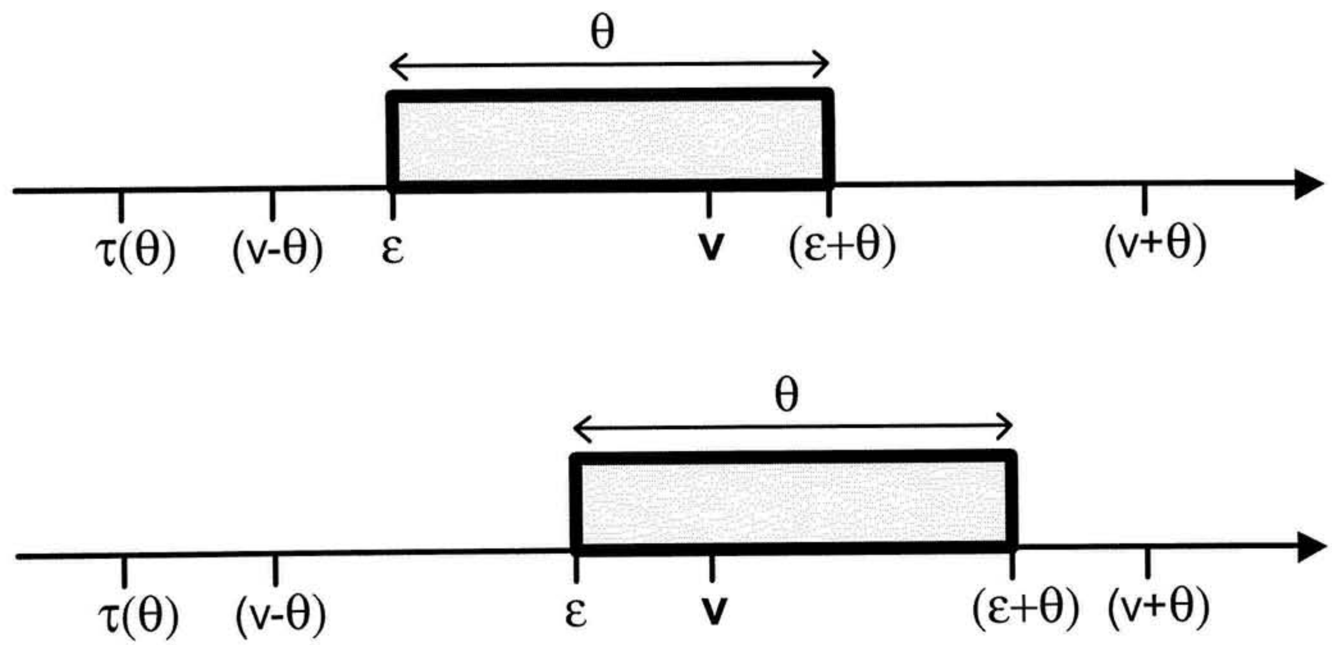


Figure 2 (a): How the intelligent agent works: the 'sliding window'

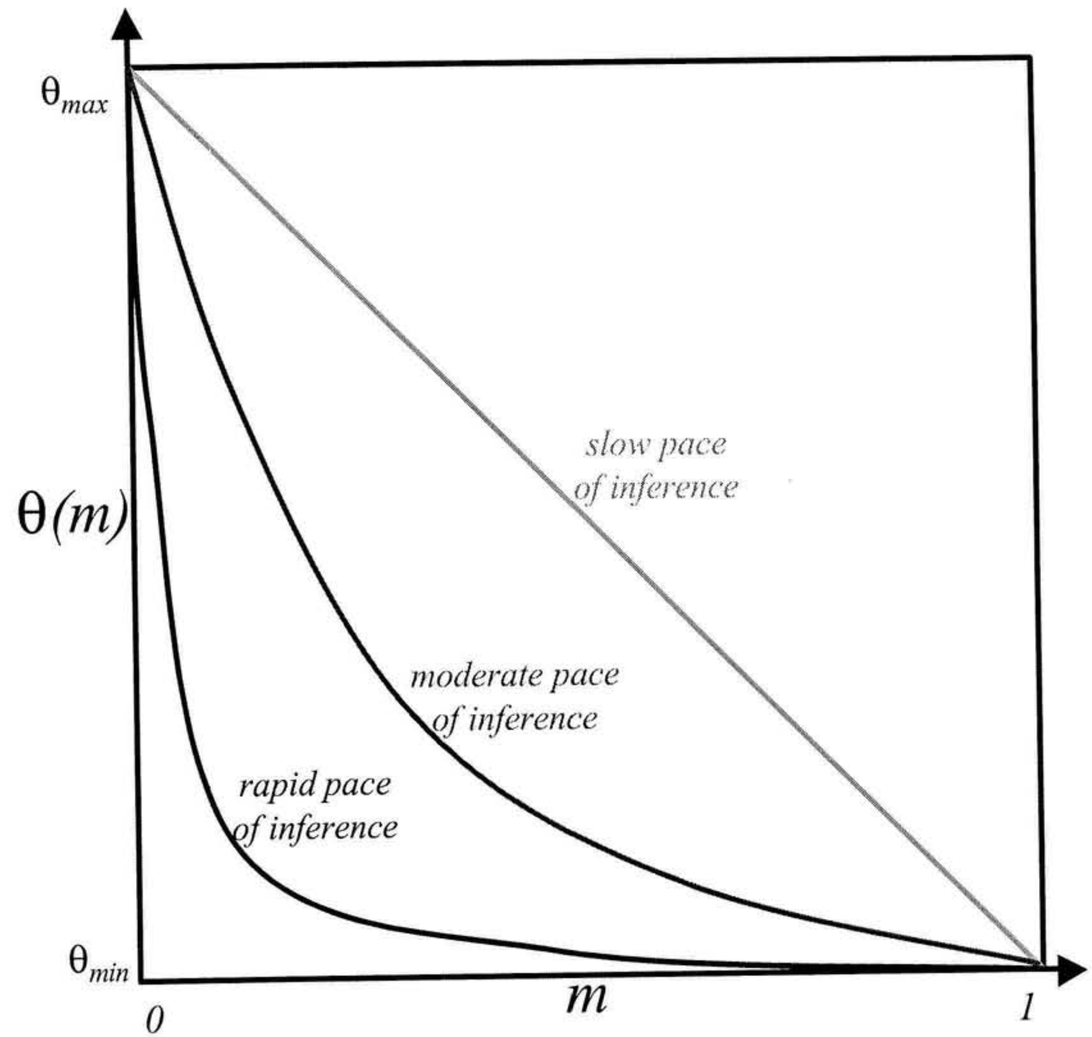


Figure 2 (b): How the intelligent agent works: the relationship between *m* and θ

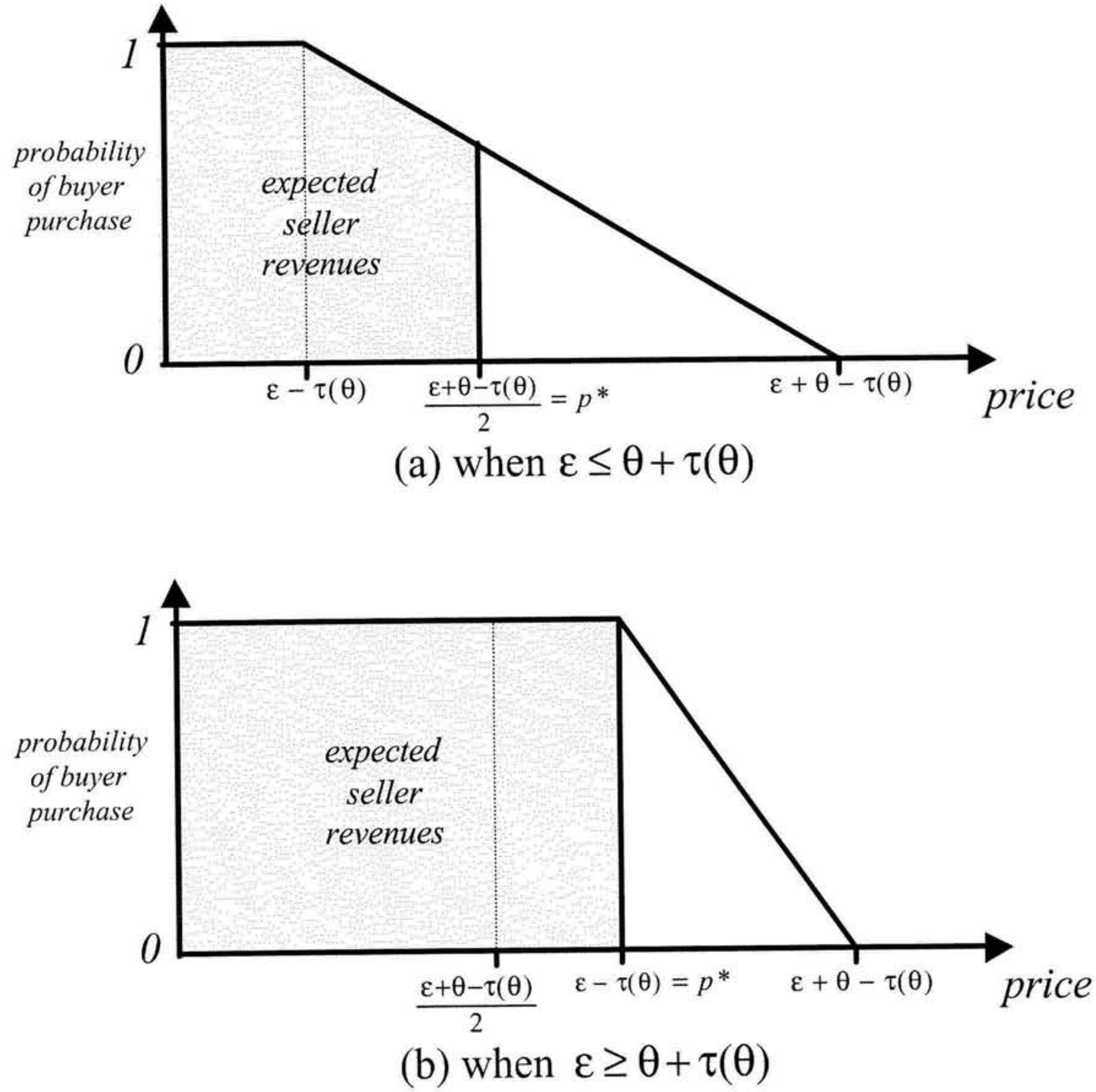
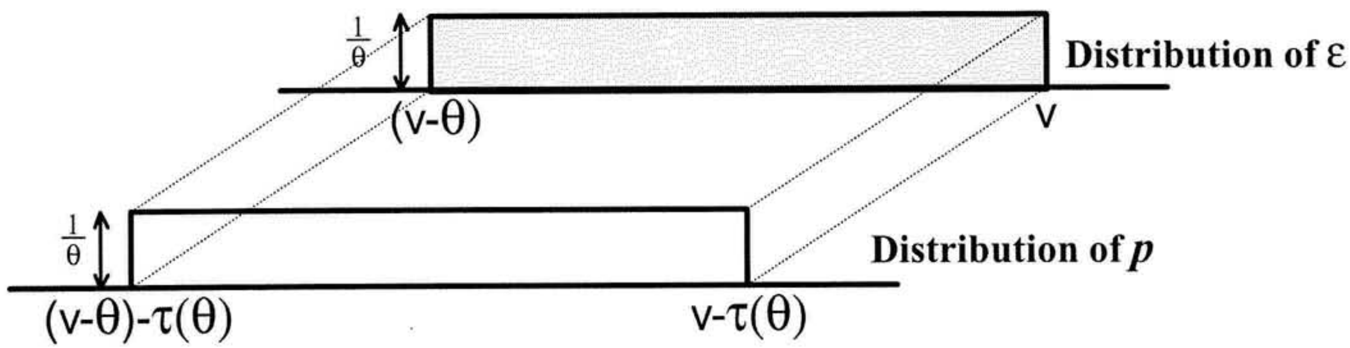
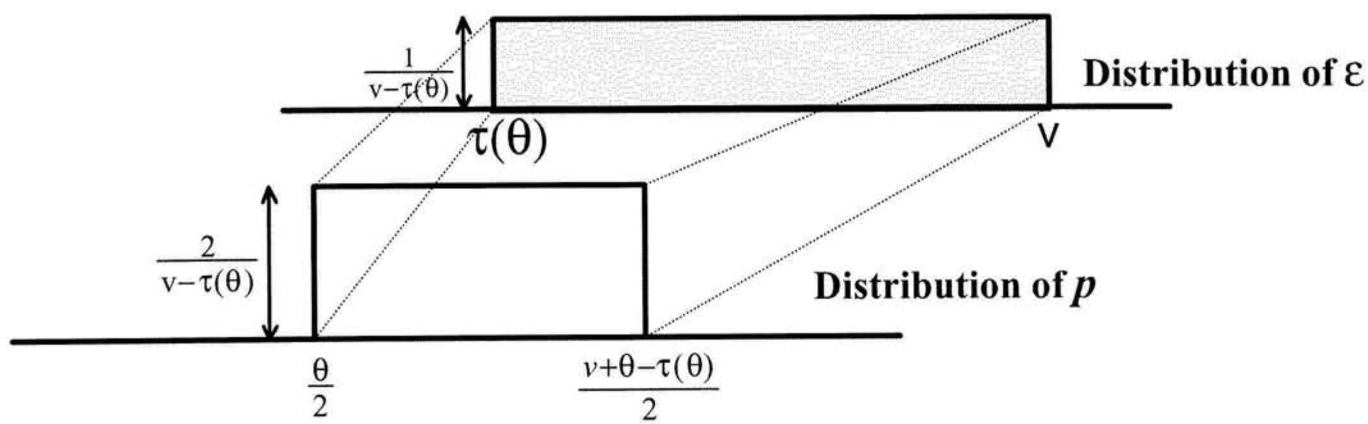


Figure 3: Optimal seller pricing

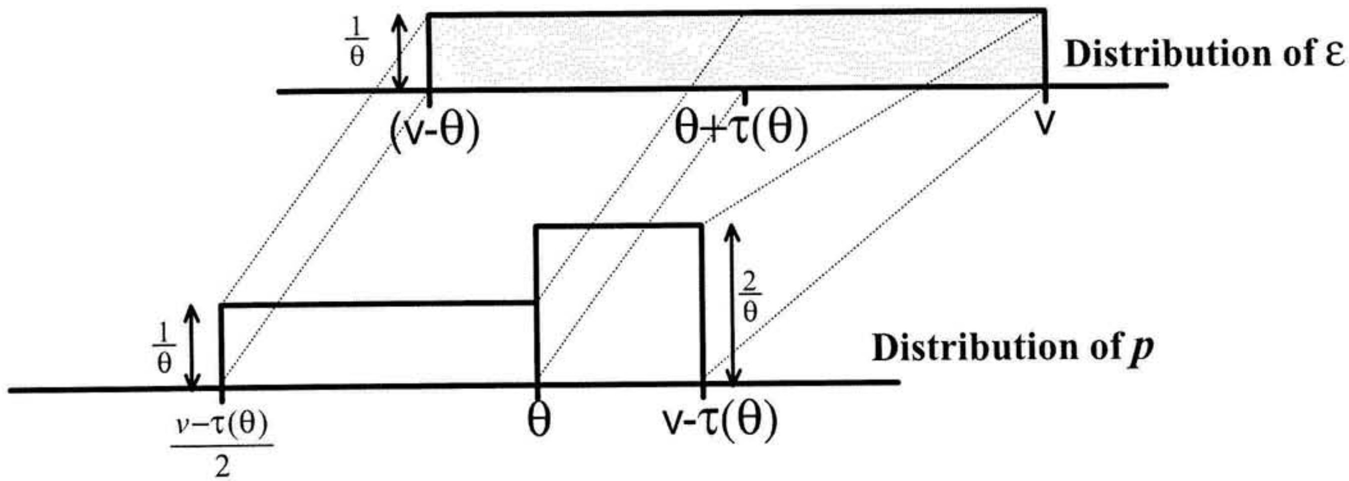


(a) For values of $\theta \leq \frac{v-\tau(\theta)}{2}$, yielding $p = \varepsilon - \tau(\theta)$



(b) For values of $\theta \geq v - \tau(\theta)$, yielding $p = \frac{\varepsilon+\theta-\tau(\theta)}{2}$

Figure 4(a) and (b): Distribution of price induced by the buyer's prior on ε



(c) For values of $\frac{v-\tau(\theta)}{2} \leq \theta \leq v - \tau(\theta)$, yielding:

$$p = \varepsilon - \tau(\theta) \text{ for } \varepsilon \leq \theta + \tau(\theta)$$

$$p = \frac{\varepsilon+\theta-\tau(\theta)}{2} \text{ for } \varepsilon \geq \theta + \tau(\theta)$$

Figure 4(c): Distribution of price induced by the buyer's prior on ε

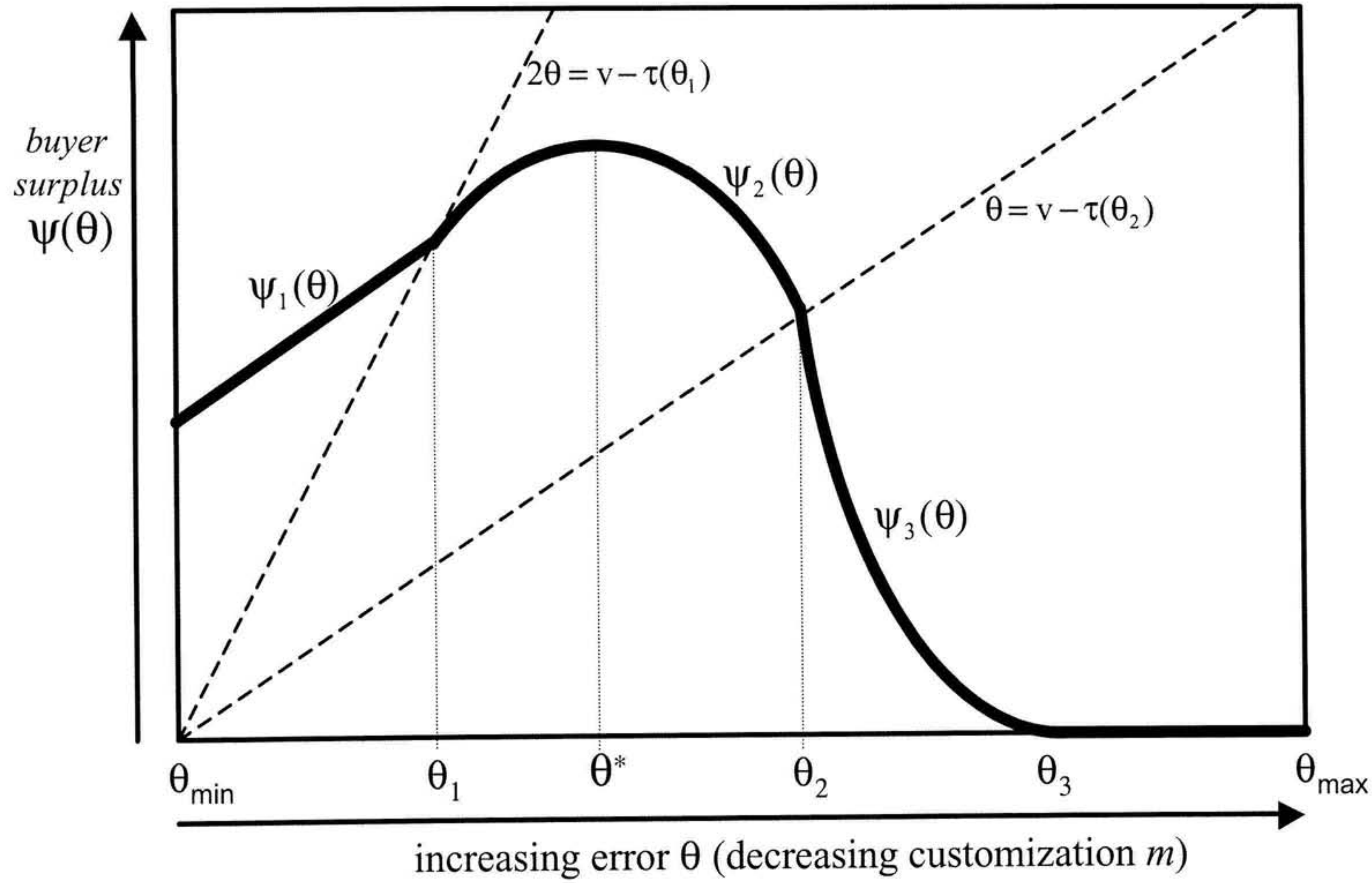


Figure 5: Buyer surplus as a function of θ

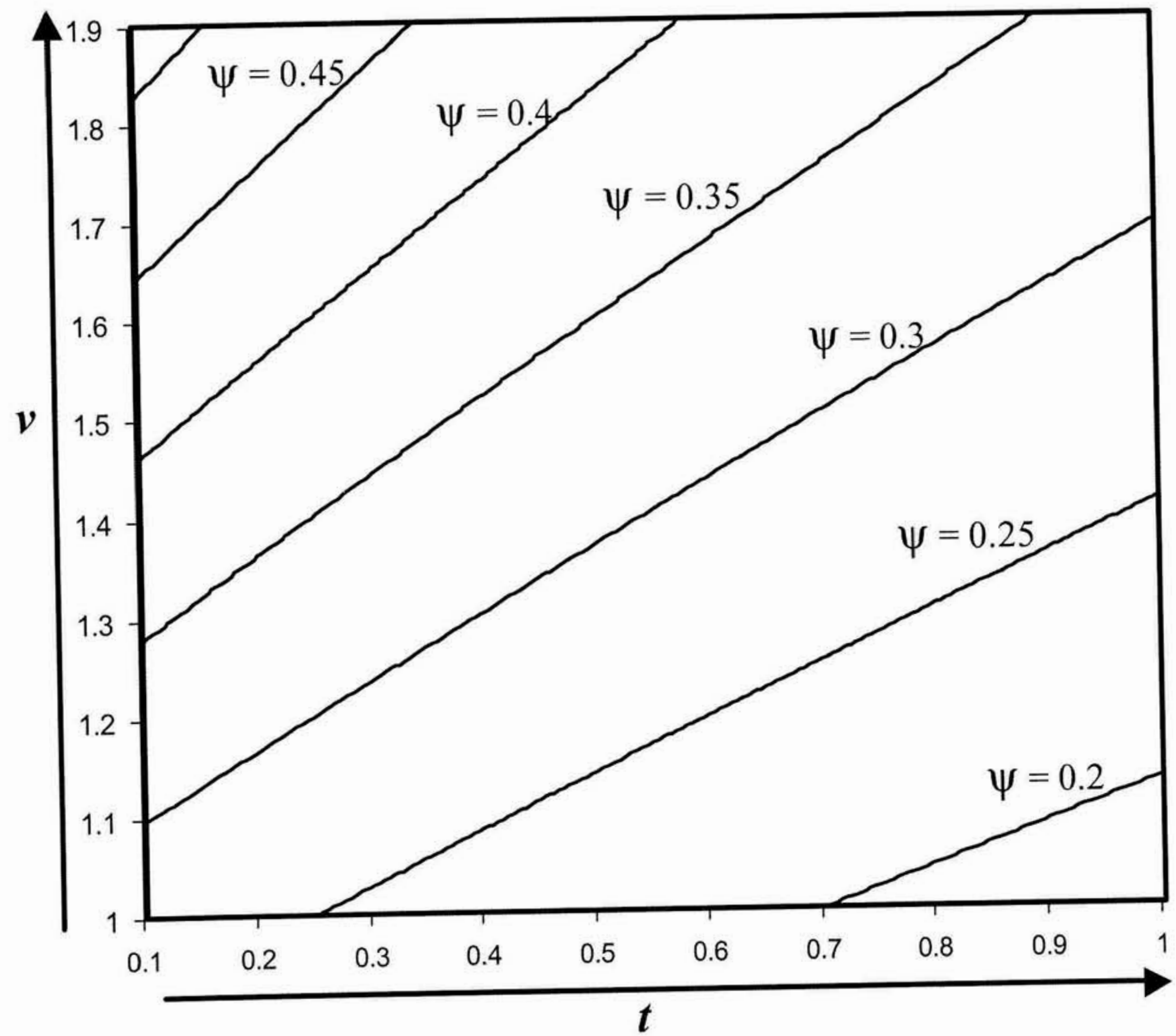


Figure 6: Iso-surplus curves for the buyer, as a function of v and t

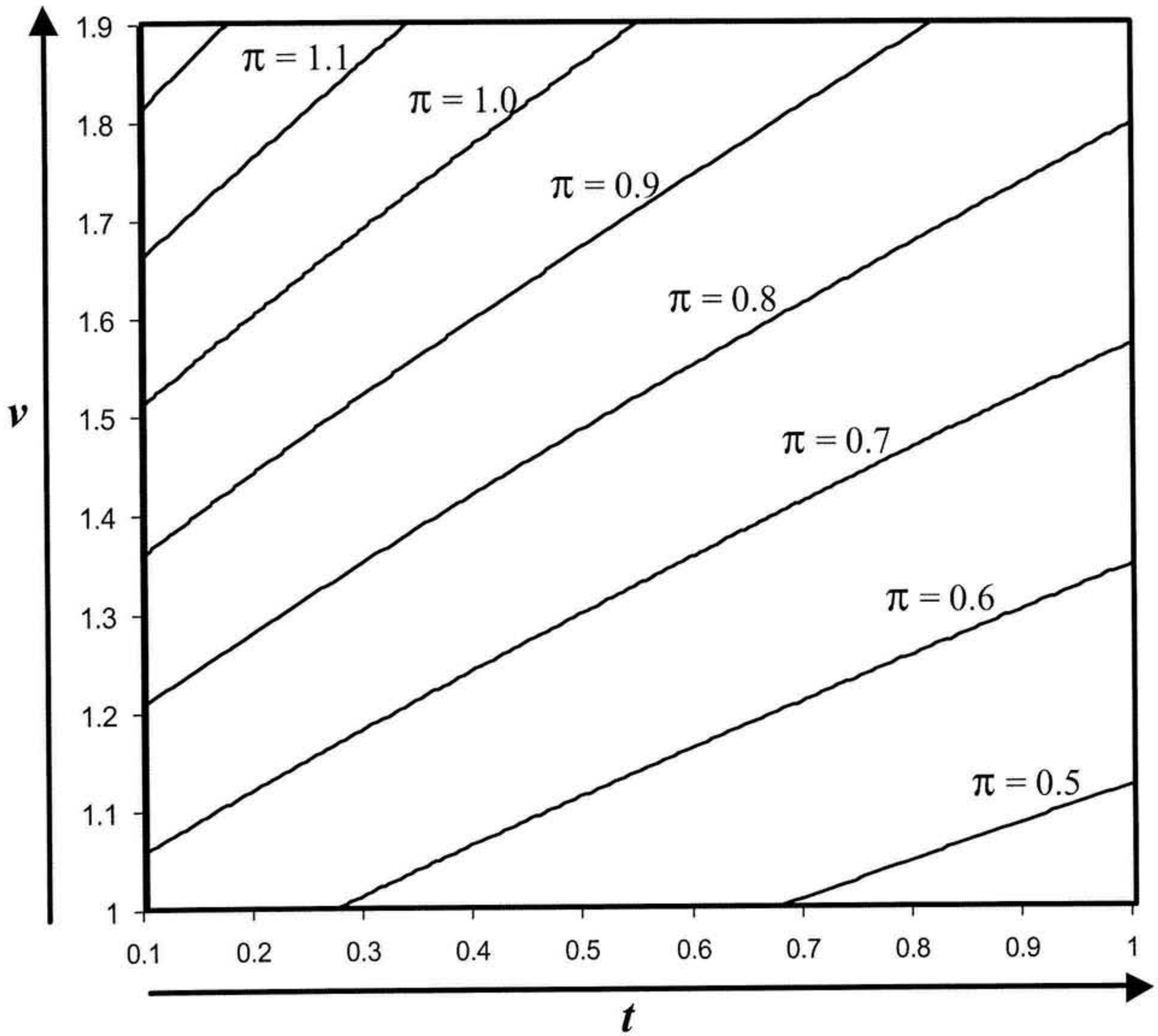


Figure 7: Isoprofit curves for the seller, as a function of v and t

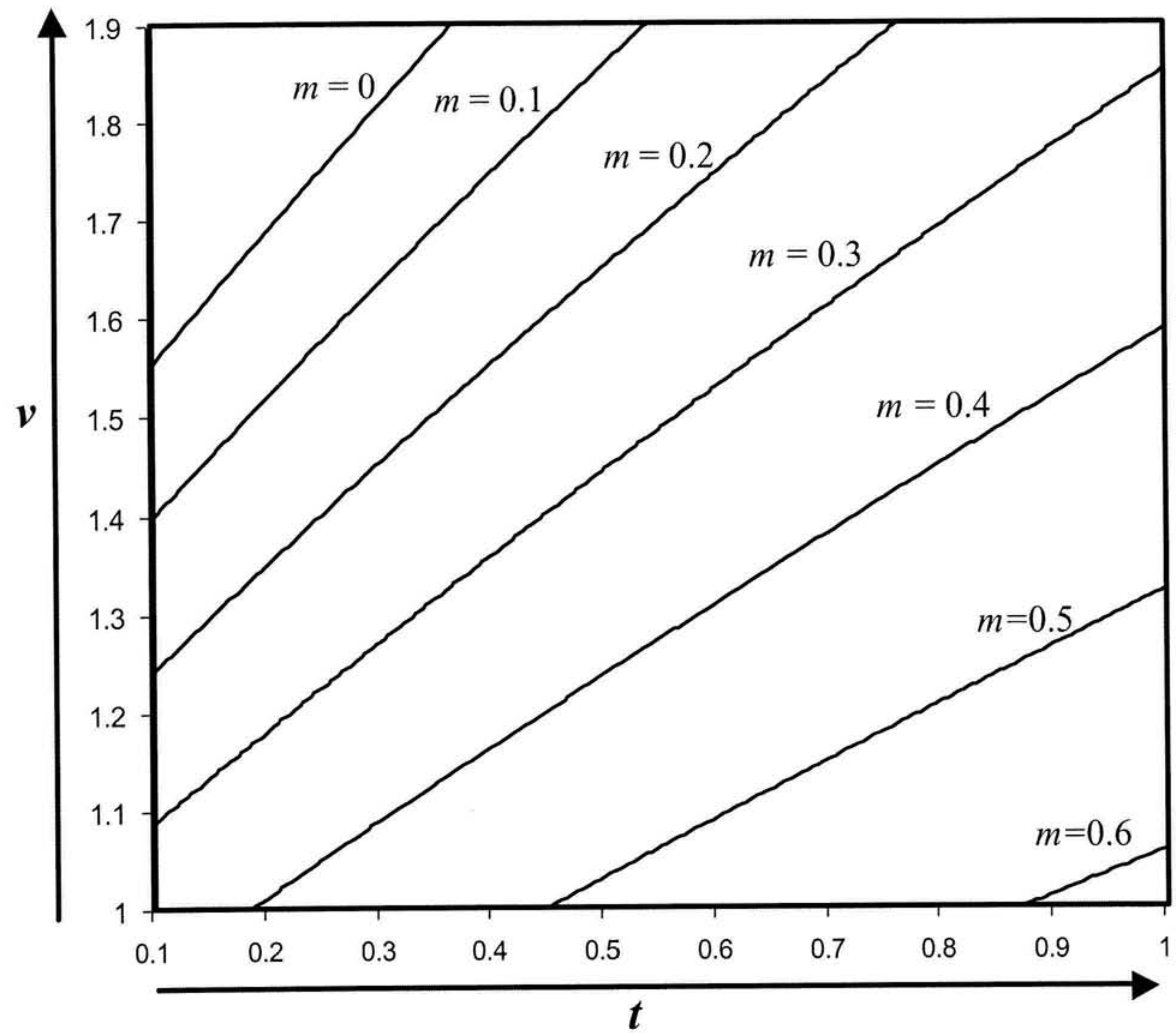
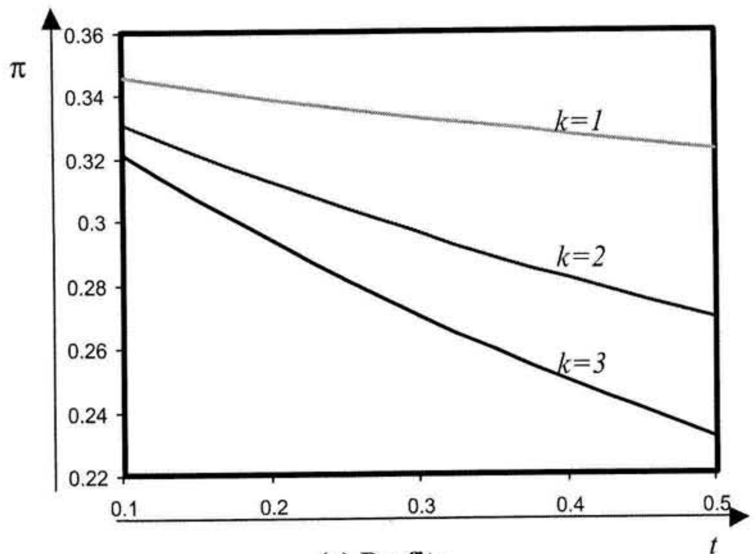
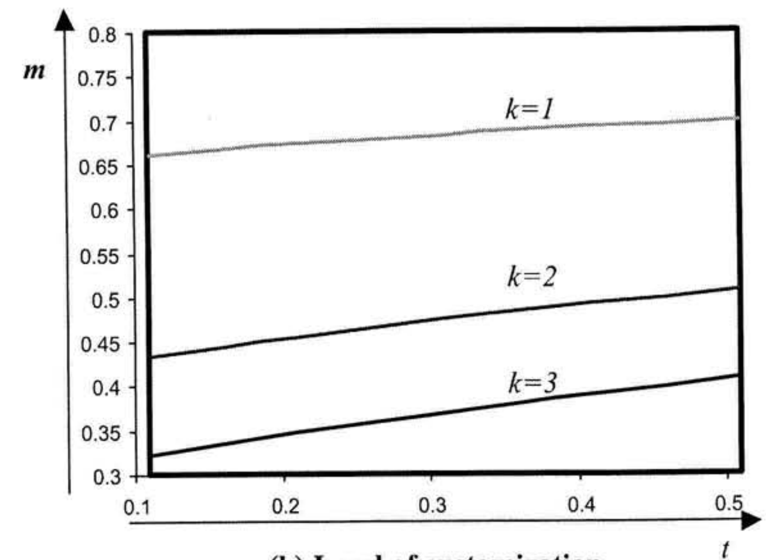


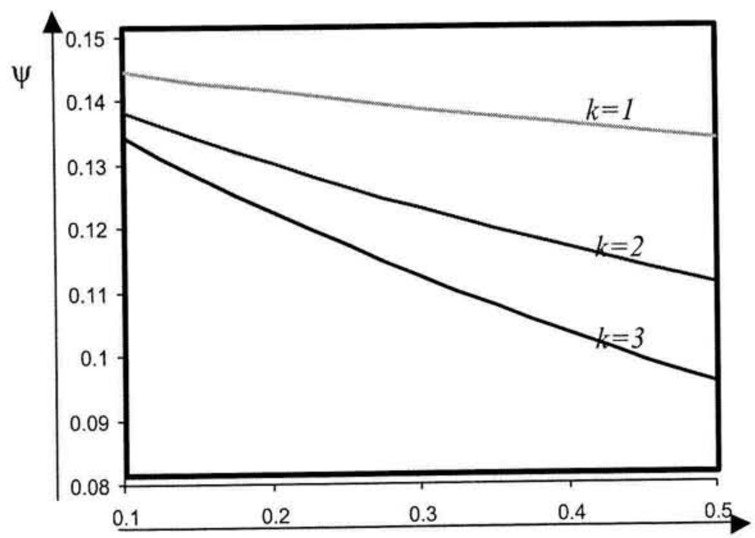
Figure 8: Iso-product (constant levels of customization m) curves for the buyer, as a function of v and t



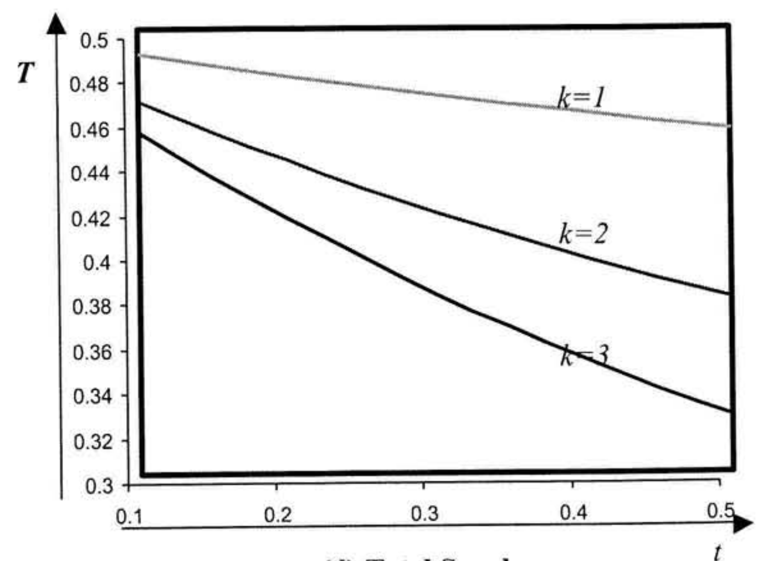
(a) Profits



(b) Level of customization

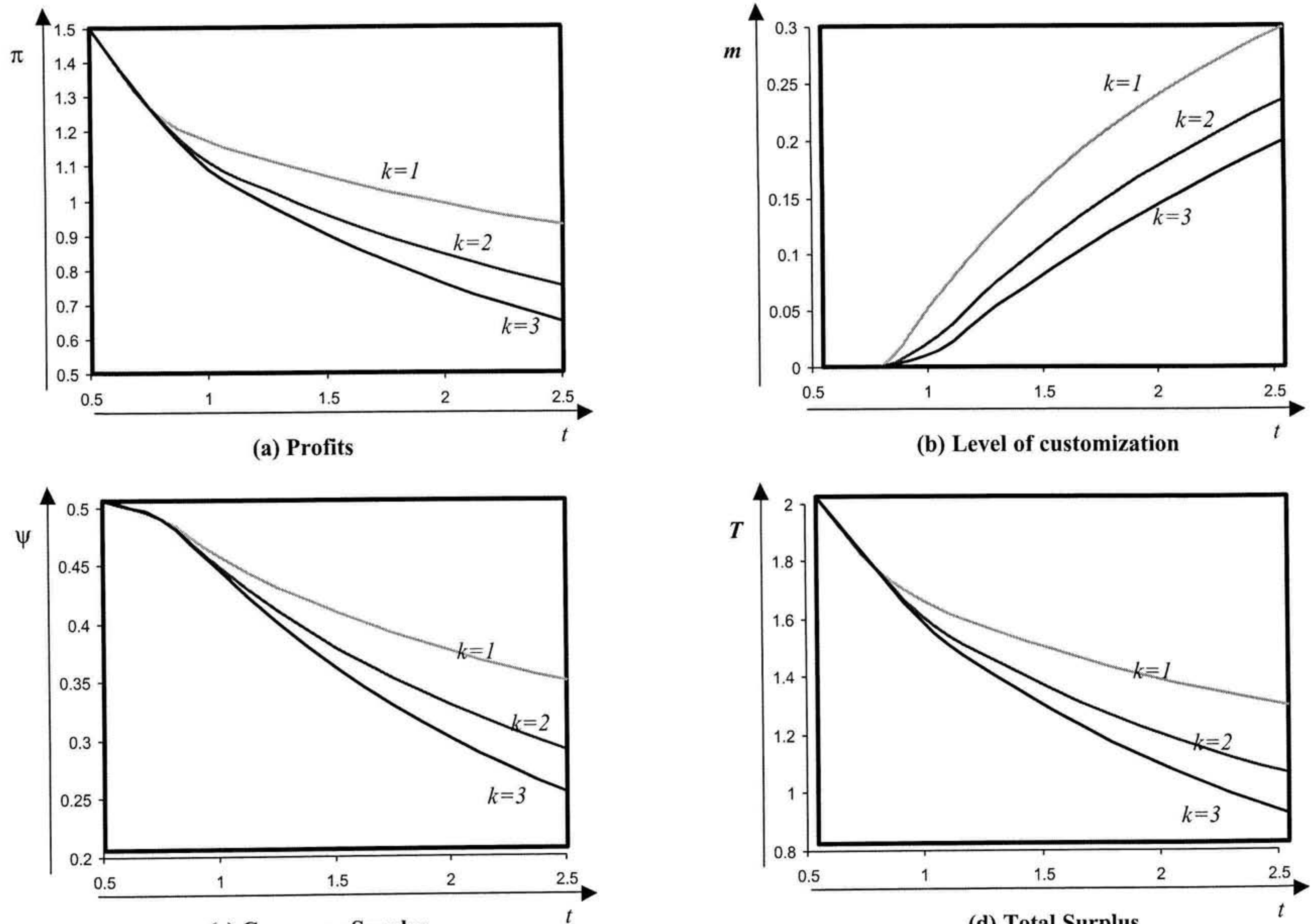


(c) Consumer Surplus



(d) Total Surplus

Figure 9: Profits, surplus and product choices – low valuation customers (v=0.5)



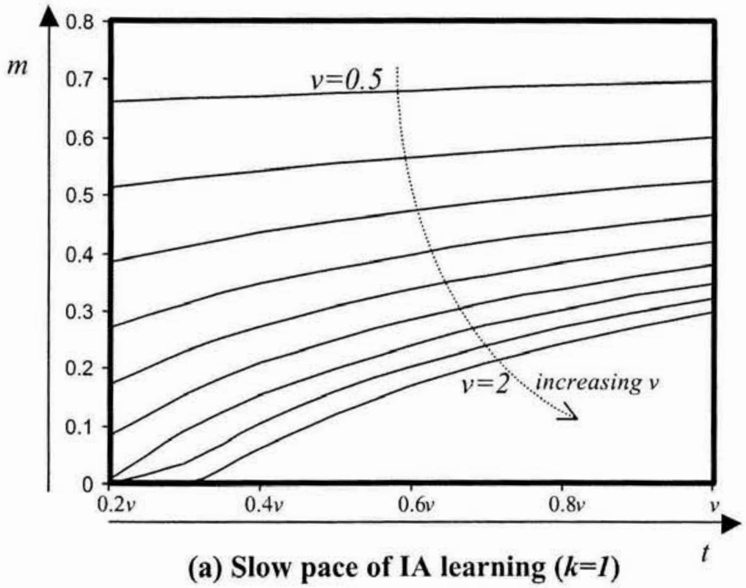
(a) Profits

(b) Level of customization

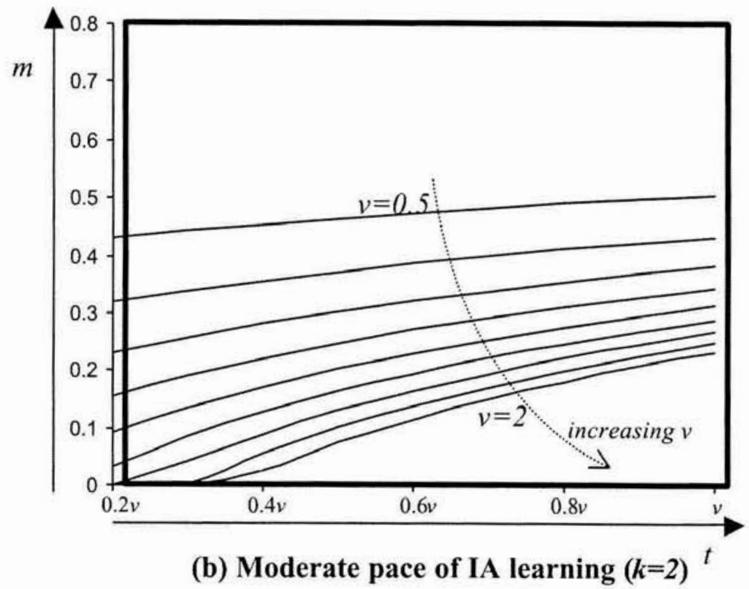
(c) Consumer Surplus

(d) Total Surplus

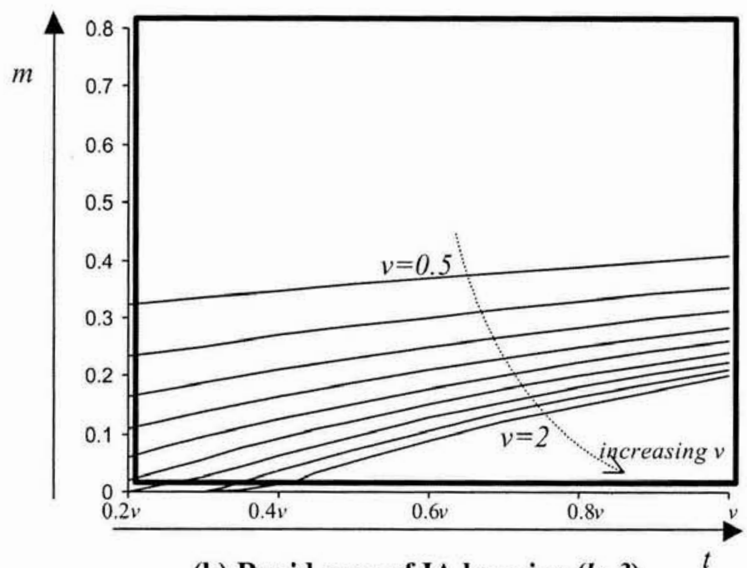
Figure 10: Profits, surplus and product choices – high valuation customers (v=2.5)



(a) Slow pace of IA learning (*k=1*)

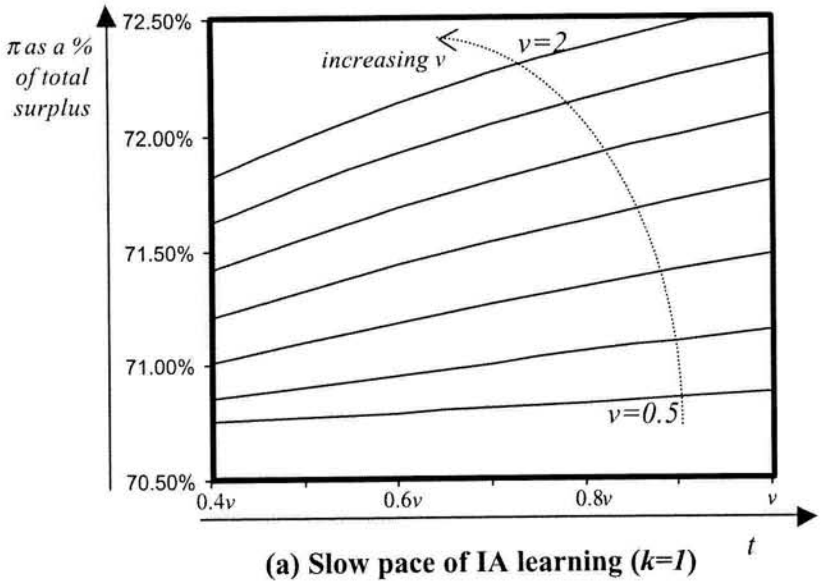


(b) Moderate pace of IA learning (*k=2*)

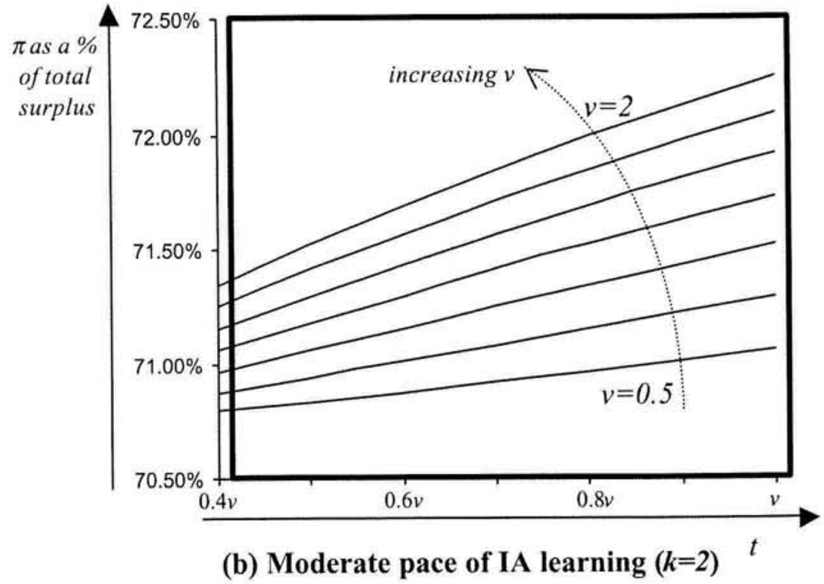


(b) Rapid pace of IA learning (*k=3*)

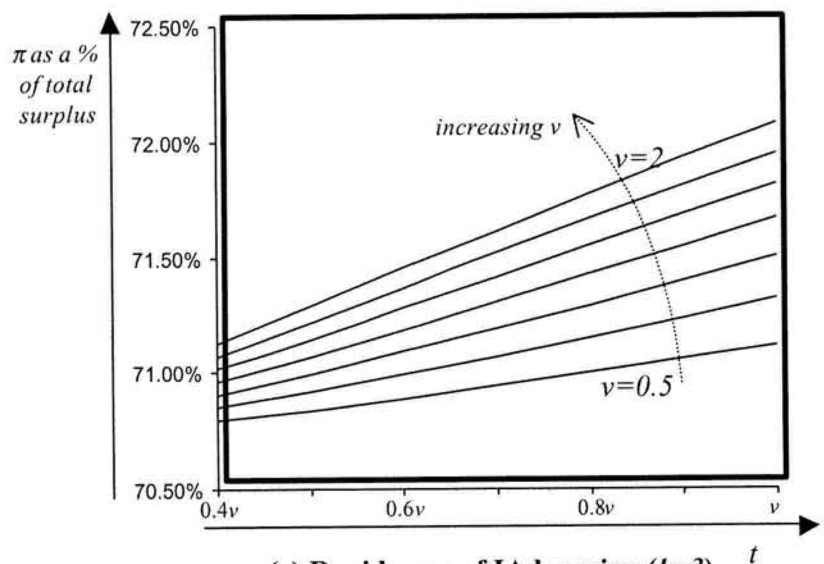
Figure 11: Product choices (levels of customization) and learning rates – a closer look



(a) Slow pace of IA learning ($k=1$)

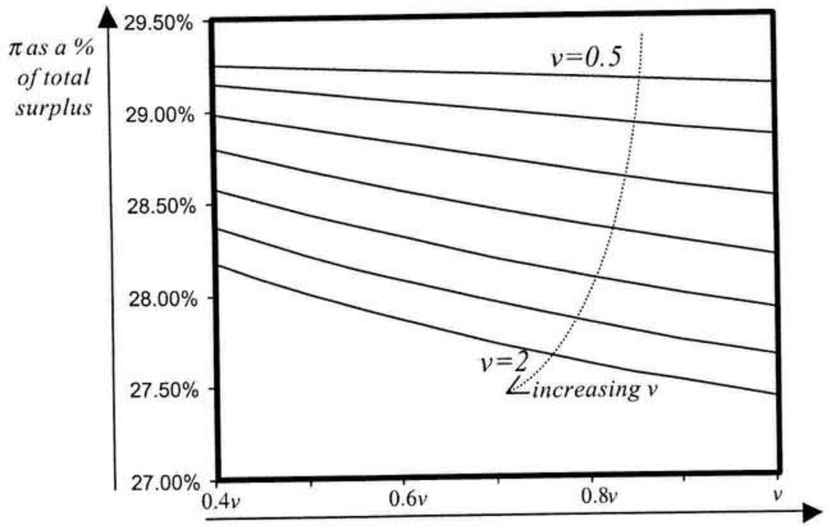


(b) Moderate pace of IA learning ($k=2$)

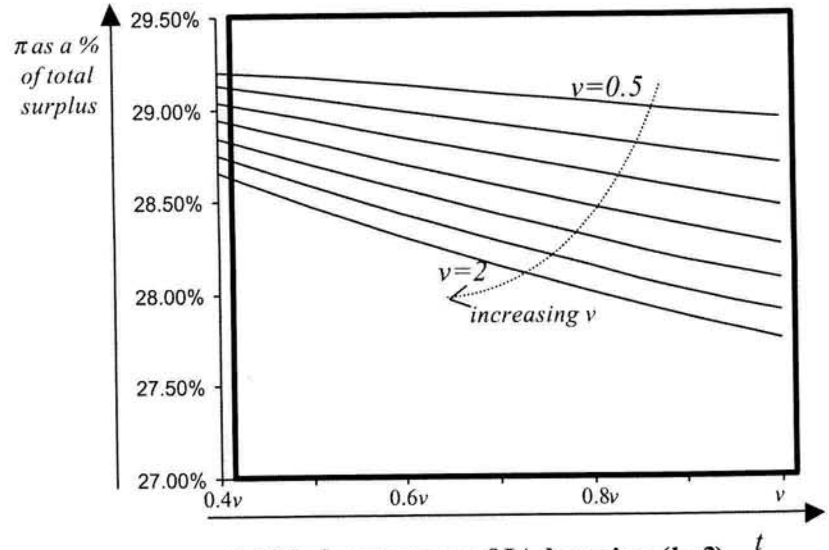


(c) Rapid pace of IA learning ($k=3$)

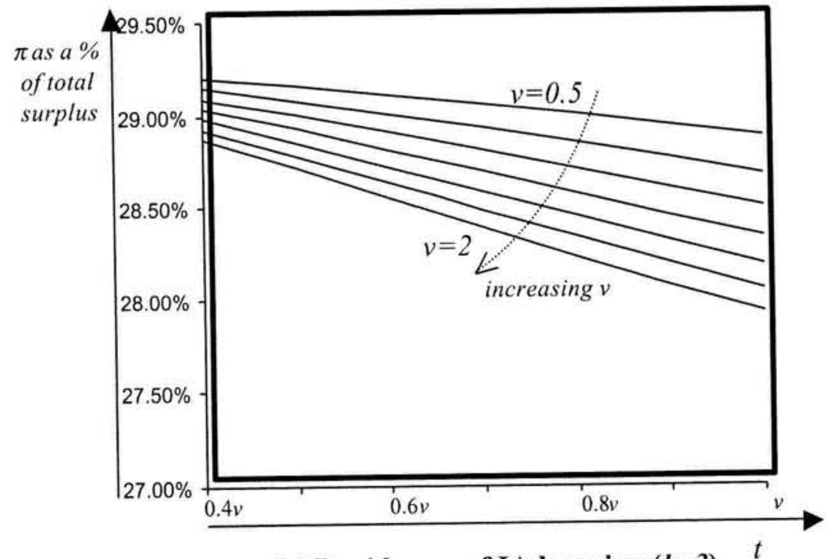
Figure 12: Seller profits as a percentage of total surplus



(a) Slow pace of IA learning (*k=1*)

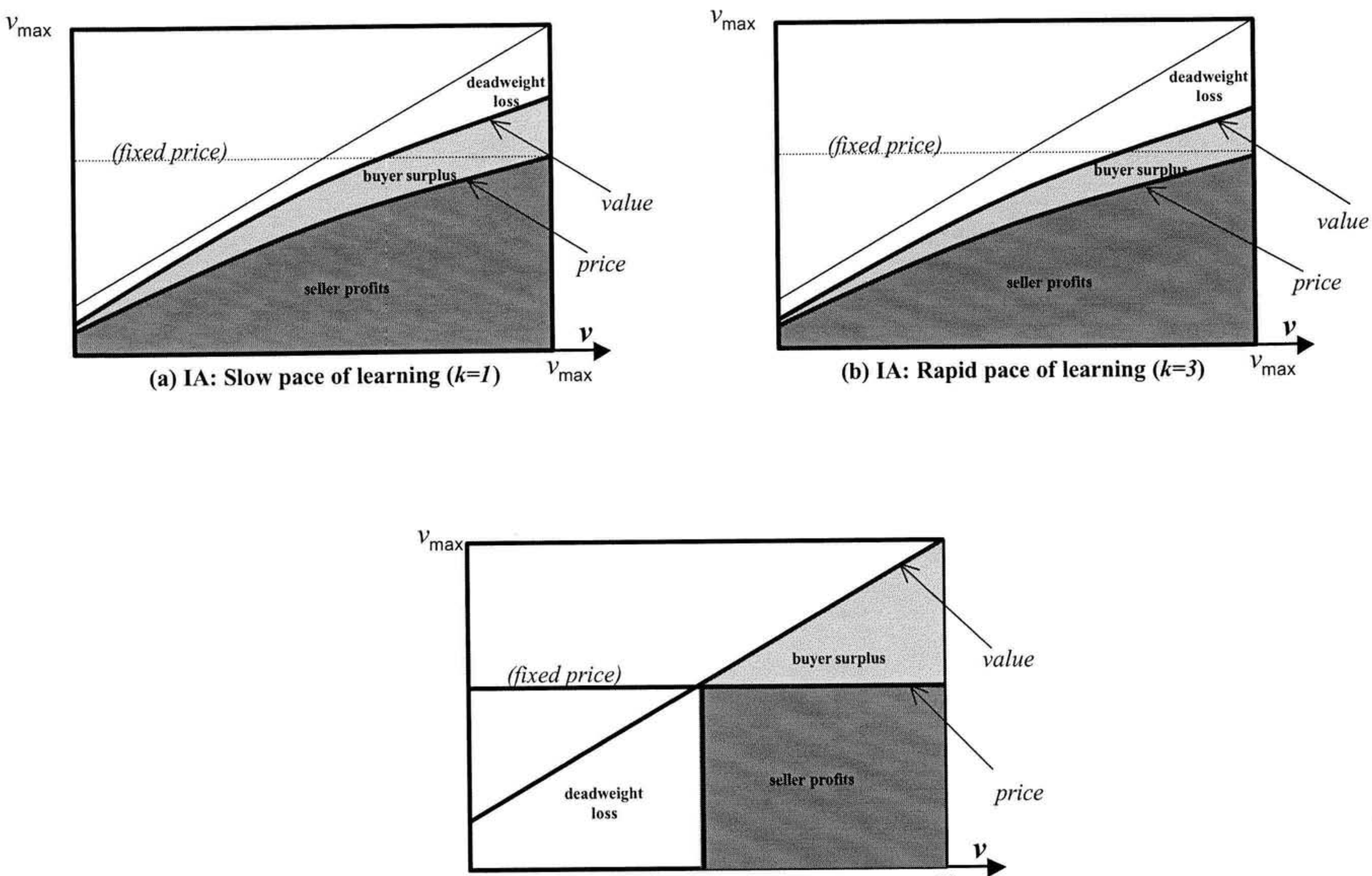


(b) Moderate pace of IA learning (*k=2*)



(c) Rapid pace of IA learning (*k=3*)

Figure 13: Buyer surplus as a percentage of total surplus



(a) IA: Slow pace of learning ($k=1$)

(b) IA: Rapid pace of learning ($k=3$)

(c) No IA: Fixed price

Figure 14: Seller profit and buyer surplus: Low cost of commiditization *t*

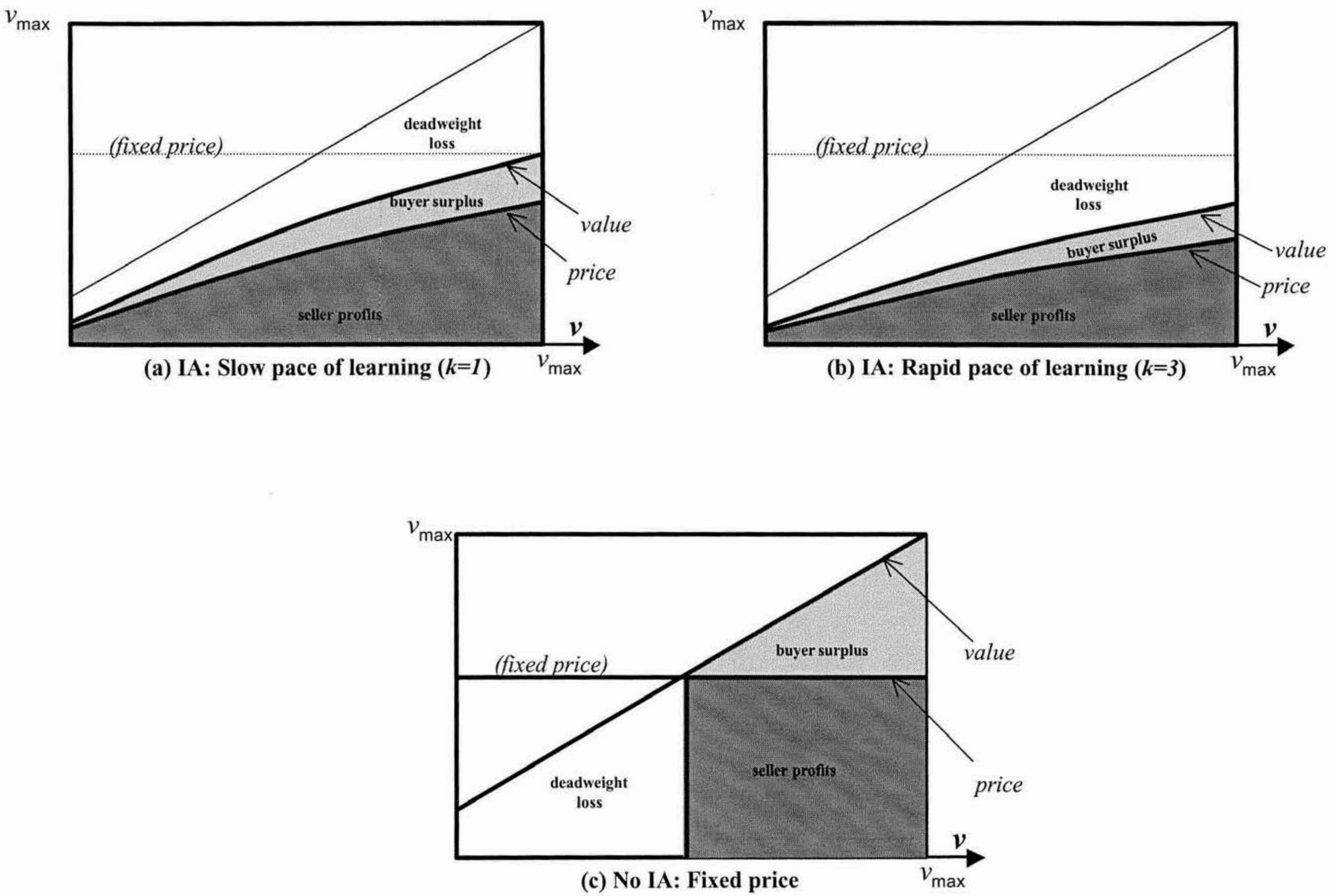


Figure 15: Seller profit and buyer surplus: High cost of commiditization *t*