



Edinburgh School of Economics
Discussion Paper Series
Number 257

Competing with Asking Prices

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Date

May 2015

Published by

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Abstract

In many markets, sellers advertise their good with an *asking price*. This is a price at which the seller will take his good off the market and trade immediately, though it is understood that a buyer can submit an offer below the asking price and that this offer may be accepted if the seller receives no better offers. Despite their prevalence in a variety of real world markets, asking prices have received little attention in the academic literature. We construct an environment with a few simple, realistic ingredients and demonstrate that using an asking price is optimal: it is the pricing mechanism that maximizes sellers' revenues and it implements the efficient outcome in equilibrium. We provide a complete characterization of this equilibrium and use it to explore the implications of this pricing mechanism for transaction prices and allocations.

Keywords: Asking Prices, Directed Search, Inspection Costs, Efficiency

JEL codes: C78, D44, D82, D83, L11, R31, R32

*We would like to thank Jim Albrecht, Gadi Barlevy, Jan Eeckhout, Andrea Galeotti, Pieter Gautier, Lu Han, Johannes Hörner, Benoit Julien, Philipp Kircher, Jonathan Levin, Guido Menzio, Peter Norman, József Sákovics, Shouyong Shi, Andy Skrzypacz, Xianwen Shi, Rob Shimer, Susan Vroman, Gábor Virág, and Randy Wright for helpful comments. All errors are our own.

[†]The views expressed here are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. This paper is available free of charge at www.philadelphiafed.org/research-and-data/publications/working-papers/.

[‡]Ludo Visschers gratefully acknowledges financial support from the Juan de la Cierva Grant; project grant ECO2010-20614 (Dirección general de investigación científica y técnica), and the Bank of Spain's Programa de Investigación de Excelencia.

[§]Ronald Wolthoff gratefully acknowledges financial support from the Connaught Fund at the University of Toronto.

“We are eager to hear ... about businesses that meet all of the following criteria:
(1) Large purchases; (2) Demonstrated consistent earning power; (3) Businesses earning good returns on equity while employing little or no debt; (4) Management in place; (5) Simple businesses; **(6) An offering price (we don’t want to waste our time or that of the seller by talking, even preliminarily, about a transaction when price is unknown)... We don’t participate in auctions.**”¹

– Berkshire Hathaway Inc., “Acquisition Criteria,” 2012 Annual Report

1 Introduction

In this paper, we consider an environment in which a trading mechanism that we call an *asking price* emerges as an optimal way of coping with certain frictions. In words, an asking price is a price at which a seller commits to taking his good off the market and trading immediately. However, it is understood that a buyer can submit an offer below the asking price and such an offer could potentially be accepted if the seller receives no better offers.² Though asking prices are prevalent in a variety of real world markets, they have received relatively little attention in the academic literature. We construct an environment with a few simple, realistic ingredients and demonstrate that using an asking price is both revenue-maximizing and efficient; that is, sellers optimally choose to use the asking price mechanism and, in equilibrium, the asking prices they select implement the solution to the planner’s problem. We provide a complete characterization of this equilibrium and use it to explore the implications of this pricing mechanism for transaction prices and allocations.

At first glance, one might think that committing to an asking price would be sub-optimal from a seller’s point of view. After all, the seller is not only placing an upper bound on the price that a buyer might propose, he is also committing not to meet with any additional prospective buyers once the asking price has been offered. Hence, when a buyer purchases the good at the asking price, the seller has forfeited any additional rents that either this buyer or other prospective buyers were willing to pay. And yet, anybody who has recently purchased a house or a car, rented an apartment, or perused the classifieds knows that an asking price seems to play a prominent role in the sale of many goods (and services). The question is: how and why can this mechanism be optimal?

¹Bold added for emphasis; italics present in original.

²What we call an asking price goes by several other names as well, including an “offering price” (as in the epigraph), a “list price” (used in the sale of houses and cars), or a “buy-it-now” or “take-it” price (used in certain online marketplaces). In many classified advertisements, what we call an asking price often comes in the form of a price followed by the comment “or best offer.” Though the terminology may differ across these various markets, along with the fine details of how trade occurs, we think our analysis identifies an important, fundamental reason that sellers might find this basic type of pricing mechanism optimal.

Loosely speaking, our answer requires two ingredients. First, the sellers in our environment *compete to attract buyers*. In particular, in contrast to the large literature that studies the performance of various trading mechanisms (e.g., auctions) when the number of buyers is fixed, we assume that there are many sellers, each one posts (and commits to) the process by which their good will be sold, and buyers strategically choose to visit only those sellers who promise the maximum expected payoff. Thus, in our framework, the number of buyers at each seller is endogenous and responds to the mechanism that the seller posts. The second ingredient is that the goods for sale are *inspection goods* and inspection is *costly*: though all sellers' goods appear ex ante identical, in fact each buyer has an idiosyncratic (private) valuation for each good which can only be learned through a process of costly inspection.³

To understand the role that each of these ingredients play, let's first consider inspection costs in isolation. When buyers have to incur a cost to learn their valuation and trade, a natural tension arises. *Ceteris paribus*, a seller wants to maximize the number of buyers who inspect his good and the offers that these buyers make. However, without any device to limit the number of buyers or the offers they make, buyers might be hesitant to approach such a seller, as the cost of inspecting the good could outweigh the potential benefits of discovering their valuation and trying to outbid all the other buyers. Instead, buyers would only incur the up-front costs of inspection if they are assured a reasonable chance of actually acquiring the good at a reasonable price.

We show that, by setting an asking price, sellers can provide buyers with this assurance. For one, an asking price implements a stopping rule, allocating the good to the first buyer who has a sufficiently high valuation, and sparing the remaining potential buyers from inspecting the good "in vain." In this sense, echoing the sentiments of Berkshire Hathaway's chairman Warren Buffett in the epigraph above, the asking price mechanism in our model serves as a promise by sellers not to waste the buyers' time and energy when they have only a small chance of actually getting the good. Moreover, by committing to sell at a particular price, a seller who uses an asking price is also assuring potential buyers that they will receive some gains from trade in the event that they discover a high valuation. For these reasons, sellers have a strong incentive to use an asking price when they are selling inspection goods.

However, they also have a strong incentive to charge buyers an admission fee to inspect their

³For example, suppose the goods are houses that are roughly equivalent along easily describable dimensions (size, general location, and so on). However, each home has idiosyncratic features that may make them more or less attractive to every prospective buyer, and these features are revealed upon inspection; e.g., an individual who likes to cook will want to examine a home's kitchen. Quite often, learning one's true valuation may require more research than is afforded by a quick tour; e.g., an individual who needs to build a home office may want to bring in an architect to get an estimate of how much it will cost. All of these activities are costly, either because they take time or because they require explicit costs (like hiring an architect). Similar costs exist for purchasing a car, renting an apartment, or even hiring an accountant. Perhaps surprisingly, these costs can even be significant for buyers purchasing goods on websites such as eBay or Craigslist, as documented by Bajari and Hortacsu (2003).

good, extracting all of the additional surplus they created by eliminating inefficient inspections. Such fees are problematic from a positive point of view, as they are rarely observed in practice. This is where our second ingredient is important: we show that, in an environment in which sellers compete to attract buyers, the optimal admission fee is, in fact, zero. Thus, in an environment with these two ingredients, sellers maximize their profits by posting a simple mechanism, composed of one asking price for all buyers, and no fees, side payments, or other rarely observed devices. Moreover, the asking price that sellers choose ultimately maximizes the expected surplus that they create, so that equilibrium asking prices implement the planner's solution.

Having provided the rough intuition, we now discuss our environment and main results in greater detail. As we describe explicitly in Section 2, we consider a market with a measure of sellers, each endowed with one indivisible good, and a measure of buyers who each have unit demand. Though goods appear *ex ante* identical, each buyer has an idiosyncratic valuation for each good and this valuation can only be learned through a costly inspection process. We assume that sellers have the ability to communicate *ex ante* (or “post”) how their good is going to be sold, and buyers can observe what each seller posts and visit the seller that offers the highest expected payoff. The search process, however, is frictional: each buyer can only visit a single seller and he cannot coordinate this decision with other buyers. As a result, the number of buyers to arrive at each seller is a random variable with a distribution that depends on what the seller posted.

As a first step, in Section 3 we characterize the solution to the problem of a social planner who maximizes total surplus, subject to the frictions described above—in particular, the search frictions and the requirement that a buyer's valuation is costly to learn. The solution has three properties. First, the planner instructs buyers to randomize evenly across sellers. Second, once a random number of buyers arrive at each seller, the planner instructs buyers to undergo the costly inspection process sequentially, preserving the option to stop after each inspection and allocate the good to one of the buyers who have learned their valuation. This strategy of “sequential search with recall” is optimal because it balances the losses associated with additional buyers incurring the inspection cost against the gains associated with finding a buyer who values the good more than all of the previous buyers. Finally, we characterize the optimal stopping rule for this strategy and establish that it is stationary; that is, it depends on neither the number of buyers who have inspected the good nor the realization of their valuations.

Next, we move on to our main contribution: we consider the decentralized economy, characterize the trading mechanism that emerges in equilibrium, and study the efficiency properties of this equilibrium. Given the nature of the planner's optimal trading protocol, the asking price mechanism is a natural candidate to implement the efficient outcome. First, since buyers' valuations are privately observed, the asking price provides sellers a channel to elicit information about these valuations. Second, since the asking price triggers immediate trade, it implements a stopping rule,

thus preventing additional buyers from incurring the inspection cost when the current buyer draws a sufficiently high valuation. Finally, since the seller also allows bids below the asking price, he retains the option to recall previous offers in which there was a positive match surplus.

These features are captured by the following game, which we study in Section 4. First, sellers post an asking price, which all buyers observe. Given these asking prices, each buyer then chooses to visit the seller (or mix between sellers) offering the maximal expected payoff. Once buyers arrive at their chosen seller, they are placed in a random order. Buyers are told neither the number of other buyers who have arrived, nor their place in the queue.⁴ The first buyer incurs the inspection cost, learns his valuation, and can either purchase the good immediately at the asking price or submit a counteroffer. If he chooses the former, trade occurs and all remaining buyers at that particular seller neither inspect the good nor consume. If he chooses the latter, the seller moves on to the second buyer (if there is one) and the process repeats until either the asking price is offered or the queue of buyers is exhausted, in which case the seller can accept the highest offer he has received.

We derive the optimal bidding behavior of buyers and the optimal asking prices set by sellers, characterize the equilibrium, and show that it coincides with the solution to the planner's problem. The fact that our asking price mechanism can implement the efficient allocation is surprising for a number of reasons, as we discuss at the end of Section 4. Chief among them, implementing the planner's allocation requires achieving efficiency along *two* margins: the allocation of the good after buyers arrive, along with the number of buyers that arrive to begin with. However our asking price mechanism affords sellers only a *single* instrument that controls both margins; the asking price determines both the ex-post allocation of the good (by implementing a stopping rule) and the ex-ante expected number of buyers (by specifying the division of the expected surplus).

After establishing that the asking price mechanism implements the solution to the planner's problem, we ask whether sellers would indeed choose to use the asking price mechanism, or if there exists an alternative mechanism that could potentially increase sellers' profits. To address this question, in Section 5 we consider a similar environment to the one described above, but we allow sellers to select from a more general set of mechanisms. In doing so, we are essentially providing sellers with the option to choose a trading protocol from a large set of extensive form games, in which they are free to make different specifications about the sequence of events, the strategies available to buyers under various contingencies, and even the *information* that buyers have when they select from these strategies.⁵ In this more general environment, we establish that

⁴As we discuss below, we consider the information made available to buyers to be an endogenous feature of the pricing mechanism.

⁵Indeed, the mechanisms that are available to sellers range from "plain vanilla" pricing schemes—such as auctions, price-posting with rationing, multilateral bargaining games, etc.—to much more complicated games, in which the rules and sequence of play, as well as the information made available to the players, could depend on the number of buyers who arrive at a seller, an individual buyer's place in the queue, the behavior of other buyers, and so on. In short, perhaps the only relevant type of trading mechanism that we do *not* allow are those that depend on the trading

the asking price mechanism we study in Section 4 maximizes a seller's payoff, regardless of the mechanisms posted by other sellers. As a consequence, there always exists an equilibrium in which all sellers use the asking price mechanism described above. Moreover, while other equilibria can exist, they are all payoff-equivalent; in particular, there is no equilibrium in which sellers earn higher expected payoffs than they do in the equilibrium with asking prices. Finally, we show that *any* mechanism that emerges as an equilibrium in this environment will resemble the asking price mechanism along most important dimensions. Therefore, though we cannot rule out potentially complicated mechanisms that also satisfy the equilibrium conditions, the fact that asking prices are both simple and commonly observed suggests that they are a robust and compelling way to deal with the frictions in our environment.

In Section 6, we flesh out just a few of the model's implications for a variety of observable outcomes. In particular, we study the level of asking prices set by sellers and the corresponding distribution of transaction prices that occur in equilibrium. We examine how these variables change with features of the environment, such as the ratio of buyers to sellers, the degree of ex ante uncertainty in buyers' valuations, and the costs of inspecting the good.

In Section 7, we discuss a few of our key assumptions, along with several interesting extensions of our basic framework. For one, we show that a simple variation of our asking price mechanism would produce a distribution of transaction prices that occur below the asking price, a mass point of transactions that occur at the asking price, *and additional transactions that occur above the asking price*. This variation, which preserves all of the normative properties reported above, could be an important step towards confronting, e.g., house prices.⁶ We also discuss how allowing for heterogeneity across goods could lead to endogenous market segmentation, where each sub-market has a different asking price, a different market tightness, and subsequently produces different patterns for prices and allocations. Finally, Section 8 concludes. The Appendix contains all proofs.

Related Literature. We contribute to the literature along two dimensions. The first is normative: we show that our asking price mechanism is both revenue-maximizing and efficient in an environment with two simple ingredients. The second is positive: we provide a rationale for the use of asking prices and explore the implications of this mechanism for equilibrium prices and allocations. Below, we compare our normative and positive results, respectively, with the existing literature.

As mentioned above, implementing the planner's allocation requires achieving efficiency along two margins. First, a seller's mechanism has to induce socially efficient search behavior by buyers;

mechanisms posted by other sellers, which is standard in this literature; such collusive behavior would seem to violate the competitive spirit that motivates our analysis.

⁶Case and Shiller (2003) and Han and Strange (2013) document that a significant fraction of real estate transactions occur at the asking price, and (in some locations) a number of transactions also occur above the asking price.

this requires that each buyer's *ex ante* expected payoff is equal to his marginal contribution to the expected surplus at that seller. Second, a seller's mechanism must maximize the surplus after buyers arrive; that is, the mechanism must ensure that the *ex post* allocation of the good is efficient. These two margins have been studied extensively in separate literatures.

The first margin is a critical object of interest in the literature on competitive (or directed) search, such as Moen (1997), Burdett et al. (2001), Acemoglu and Shimer (1999), and Julien et al. (2000), to name a few. While these papers have often found that the market equilibrium decentralizes the planner's solution, their results do not extend to our environment. The reason is that, in these papers, the size of the surplus after buyers arrive is independent of the pricing mechanism. Hence, a simple mechanism, like a price or a wage, can control the division of the expected surplus in an arbitrarily flexible way without any ramifications for *ex post* efficiency. Therefore, within this literature, the papers that are most related to our work are McAfee (1993), Peters and Severinov (1997), Burguet and Sákovics (1999), Eeckhout and Kircher (2010), Virág (2010), Kim and Kircher (2015), Albrecht et al. (2012), and Lester et al. (2015), who consider environments where the pricing mechanism that is posted *does* effect the size of the surplus after buyers arrive. However, in these papers the *ex post* efficient allocation of the good is typically fairly trivial, and hence can be implemented with a simple, simultaneous mechanism (like an auction with no reserve price).

In contrast, our model—where buyers incur a cost to learn their valuation—requires that we consider a competitive search model where sellers post *sequential* mechanisms; to the best of our knowledge, this is the first paper to do so. We establish that the mechanism that achieves the efficient *ex post* allocation also induces efficient search decisions by buyers *ex ante*.

Sequential mechanisms have received much more attention in the literature that focuses on the second margin highlighted above but abstracts from the first margin, i.e., the literature that studies the allocation of a good when a monopolist seller faces a fixed number of buyers who can learn their valuation at a cost. However, the prevailing wisdom in this literature is that the optimal mechanism in this environment will require that the seller have access to a number of different instruments. For instance, within this literature, the paper that is closest to ours is Crémer et al. (2009); indeed, the problem that *each* seller in our environment faces is analyzed as a special case in their paper. They show that, in this setting, the seller optimally selects a sequential mechanism that requires a series of different take-it-or-leave-it offers and participation fees, both of which may vary according to the number and realizations of previous bids.⁷ Deeming such a mechanism implausibly elaborate and demanding, Bulow and Klemperer (2009) instead focus on two “plain

⁷These take-it-or-leave-it offers act like a sequence of asking prices which, along with participation fees, are calibrated just right to extract all of the buyers' surplus. In a similar environment, Burguet (1996) also shows that one way to implement the efficient allocation is through a relatively complicated sequence of reserve prices and bidding subsidies.

vanilla” mechanisms—a simultaneous auction and a simple sequential mechanism—and identify a trade-off between revenue-maximization and efficiency.

In contrast to these papers, the mechanism we consider is relatively simple—sellers post a single number—and yet the trade-off in Bulow and Klemperer (2009) does not arise; the asking price is both revenue-maximizing and efficient.⁸

The reason for this difference is twofold. First, it turns out that the information made available to buyers has important effects on the structure of the optimal mechanism. Crémer et al. (2009) and Bulow and Klemperer (2009) assume that prospective buyers observe both the number and behavior of previous bidders who have entered the mechanism, which implies that the optimal mechanism offers different asking prices (and charges different fees) to each buyer who inspects the good. We allow the sellers in our model to control what information is available to buyers, and they choose not to reveal information about previous bidders. This change alone implies that sellers would set the same asking price for all buyers, albeit with an admission fee attached.⁹ The second reason our results are different is that the number of buyers who can potentially inspect a seller’s good is exogenous in the papers cited above, whereas in our model it is the endogenous outcome of a game in which sellers compete for buyers. In this competitive setting, as we noted earlier, admission fees are driven to zero in equilibrium.¹⁰

Turning to the positive results, our explanation is of course not the only plausible reason why asking prices might serve a useful role.¹¹ For one, if buyers are risk averse, an asking price offers a way of reducing the uncertainty an individual buyer faces in certain (not necessarily optimal) types of auctions, and hence introducing this mechanism can potentially increase a seller’s revenues; see, e.g., Budish and Takeyama (2001), Mathews (2004), or Reynolds and Wooders (2009). A

⁸Roberts and Sweeting (2013) also compare the performance of a simultaneous auction and a simple sequential mechanism, though they assume buyers have some information about their valuation before making an entry decision. Interestingly, the asking price mechanism in our model convexifies, in a way, the binary choice between these two pricing schemes; as we discuss below, one can interpret our mechanism in such a way that the asking price determines the probability of having an auction (after all buyers have inspected the good) as opposed to a sequential sale.

⁹The relevant issue, then, is whether sellers can prevent buyers from observing the number of other buyers that have inspected the good and their bids. Obviously, in some cases this is possible and in other cases it is not. In this sense, our results are best viewed as complementary to those of Crémer et al. (2009) and Bulow and Klemperer (2009). We discuss the role of the information structure in greater detail in Section 4.

¹⁰In a different environment, Peters (2001) also finds that sellers who would charge positive admission fees in a monopolistic setting optimally choose not to charge fees in a competitive setting. It is also worth noting that a similar insight emerges from models that study the problem of a single seller who selects a mechanism to sell a good, and a large number of buyers who can choose to participate in the mechanism at a cost; see, e.g., Engelbrecht-Wiggans (1987), McAfee and McMillan (1987), and Levin and Smith (1994). The only difference is that the “cost” to a buyer from visiting a seller in a competitive search model is the opportunity cost of not visiting other sellers, which is an equilibrium object, while the cost of participating in these models with one seller is an explicit entry cost, which is exogenous.

¹¹A different, but related, pricing mechanism is one where sellers offer a discounted price to buyers who purchase the good immediately, which is intended to deter buyers from continuing to search for a better price; see, e.g., Armstrong and Zhou (2014).

second explanation for asking prices, which also assumes that it is costly for buyers to learn their valuation, is proposed by Chen and Rosenthal (1996) and Arnold (1999). In their environment, a holdup problem emerges when a buyer and seller bargain over the terms of trade after the buyer incurs the inspection cost. An asking price is treated as a ceiling on the bargaining outcome and thus partially solves this holdup problem by serving as an *ex ante* guarantee that some rents will be transferred from the seller to the buyer. Hence, our paper is similar in that we also study how a seller's commitment to a pricing mechanism can induce buyers to inspect when they otherwise would not. However, there are a number of important differences as well: in our model, a seller's pricing decision also effects the number of buyers who arrive to inspect the good and the allocation of the good after inspections occur. Moreover, we show that the asking price is optimal for sellers given almost any mechanism one could imagine, while it's not clear in Chen and Rosenthal (1996) whether the mechanism they consider is the best way to solve the holdup problem they describe.¹²

A trading mechanism that bears some resemblance to an asking price can also emerge if it is costly for sellers to meet with each buyer, as in McAfee and McMillan (1988). In this case, the price that sellers advertise serves as a commitment device to *keep meeting* with buyers until a sufficiently high bid has been received, despite an incentive *ex post* to stop earlier. Hence, this quoted price is playing the opposite role as the asking price in our model; according to our explanation, asking prices serve as a promise to *stop sampling* after a sufficiently high bid, despite an incentive *ex post* to continue.¹³

Finally, asking prices may serve as a device to signal sellers' private information. For example, in Albrecht et al. (2015), sellers with heterogeneous reservation values use asking prices to signal their type, which allows for endogenous market segmentation. We view this line of research as complementary to our own; certainly the ability of asking prices to signal a seller's private information, which we ignore, is important.¹⁴

¹²More generally, the various theories of asking prices described above all consider the problem of a seller in isolation. Therefore, though each one certainly captures a significant component of what asking prices do, they also abstract from something important: the fact that buyers can observe and compare multiple asking prices at once is not only realistic in many markets, but also seems to be a principal consideration when sellers are determining their optimal pricing strategy.

¹³To be more precise, McAfee and McMillan (1988) consider a procurement auction in which a buyer meets with a sequence of sellers and each meeting is costly to the buyer; this is equivalent to our environment with the seller incurring the cost of each meeting. Switching which party bears the inspection cost not only changes the entire rationale for an asking price, as described above, but it also changes the nature of the revenue-maximizing mechanism; the solution to our model with this alternative cost structure is available upon request.

¹⁴Menzio (2007), Delacroix and Shi (2013), and Kim and Kircher (2015) also study the signalling role of prices in directed search equilibria. However, in papers like Albrecht et al. (2015) and Menzio (2007), asking prices are not uniquely determined, and hence these models are somewhat limited in their ability to draw positive implications about the relationship between asking prices, transaction prices, and market conditions.

2 The Environment

Players. There is a measure θ_b of buyers and a measure θ_s of sellers, so that $\Lambda = \theta_b/\theta_s$ denotes the ratio of buyers to sellers. Buyers each have unit demand for a consumption good, and sellers each possess one, indivisible unit of this good. All agents are risk-neutral and ex ante homogeneous.

Search. Buyers can visit a single seller in attempt to trade. Frictions arise because buyers cannot coordinate with one another when choosing a seller to visit, but rather they must use symmetric strategies.¹⁵ As a result, the number of buyers to arrive at each seller, n , will be distributed according to a Poisson distribution.¹⁶ As is customary in the literature on directed (or competitive) search, we will refer to the expected number of buyers to arrive at a particular seller as the “queue length,” which we denote by λ . As we describe in detail below, the queue length at each seller will be an endogenous variable, determined by the equilibrium behavior of buyers and sellers.

Preferences. All sellers derive utility y from consuming their own good, and this valuation is common knowledge. A buyer’s valuation for any particular good, on the other hand, is not known ex ante. Rather, once buyers arrive at a particular seller, they must inspect the seller’s good in order to learn their valuation, which we denote by x . We assume that each buyer’s valuation is an iid draw from a distribution $F(x)$ with support in the interval $[\underline{x}, \bar{x}]$, and that the realization of x is the buyer’s private information.

We assume, for simplicity, that $y \in [\underline{x}, \bar{x}]$. This is a fairly weak assumption; the probability that a buyer’s valuation x is smaller than y can be driven to zero without any loss of generality. Moreover, much of the analysis remains similar when $y < \underline{x}$, though the algebra is slightly more involved.

Inspection Costs. A key friction in the model is that the process of inspecting a good is costly to the buyer. In particular, after a buyer arrives at a seller, we assume that he must pay a cost k in order to learn his valuation x . As we discussed in footnote 3, such costs come in many forms, both explicit (i.e., paying for an inspection) and implicit (i.e., the time it takes to learn one’s valuation); we use k to capture all of these costs.

We restrict our attention to the region of the parameter space in which the cost of inspecting

¹⁵This assumption is often motivated by the observation that coordination among anonymous buyers in a large market seems fairly implausible.

¹⁶More precisely, the Poisson distribution arises as the limit of an urn-ball specification with a finite number of agents in which each buyer chooses a single seller, but buyers are restricted to symmetric strategies. See, e.g., Burdett et al. (2001).

the good does not exhaust the expected gains from trade. In particular, we assume that

$$k < \int_y^{\bar{x}} (x - y) f(x) dx. \quad (1)$$

Note that the inequality in (1) does not necessarily imply that a buyer would always *choose* to inspect the good. In what follows, we will assume that a buyer indeed does have incentive to inspect the good before attempting to purchase it, and in Section 7 we derive a sufficient condition to ensure that this is true in equilibrium.

Gains from Trade. When n buyers arrive at a seller, the trading protocol in place will determine how many buyers $i \leq n$ will have the opportunity to inspect the good before exchange (potentially) occurs. We normalize the payoff for a buyer who does not inspect, and thus does not trade, to zero. Therefore, if a buyer with valuation x acquires the good after the seller has met with i buyers, the net social surplus from trade is $x - y - ik$. Alternatively, if the seller retains the good for himself after i inspections, the net social surplus is simply $-ik$.

3 The Planner's Problem

In this section, we will characterize the decision rule of a (constrained) benevolent planner whose objective is to maximize net social surplus, subject to the constraints of the physical environment. These constraints include the frictions inherent in the search process, as well as the requirement that buyers' valuations are costly to learn.

The planner's problem can be broken down into two components. First, the planner has to assign queue lengths of buyers to each seller, subject to the constraint that the sum of these queue lengths across all sellers cannot exceed the total measure of available buyers, θ_b . Second, the planner has to specify the trading rules for agents to follow after the number of buyers that arrive at each seller is realized. We discuss these specifications in reverse order.

Optimal Trading Protocol. Suppose n buyers arrive at a seller. As is well-known in the literature (see e.g. Lippman and McCall, 1976; Weitzman, 1979; Morgan and Manning, 1985), it is optimal in this case for the planner to let buyers inspect the good sequentially, and to assign the good immediately whenever a buyer's valuation exceeds a cutoff, x^* , which equalizes the marginal cost of an additional inspection with the marginal benefit. Importantly, note that the cutoff does not depend on the total number of buyers n , the number of buyers who have inspected the good so far i , or the history of valuations (x_1, \dots, x_i) . The following lemma formalizes this result.

Lemma 1. *Suppose $n \in \mathbb{N}$ buyers arrive at a seller. Letting x^* satisfy*

$$k = \int_{x^*}^{\bar{x}} (x - x^*) f(x) dx, \quad (2)$$

the planner maximizes social surplus by implementing the following trading rule:

- (i) *If $n > 1$ and $i \in \{1, 2, \dots, n-1\}$, the seller should stop meeting with buyers and allocate the good to the agent with valuation $\hat{x}_i \equiv \max\{y, x_1, \dots, x_i\}$ if, and only if, $\hat{x}_i \geq x^*$. Otherwise, the seller should meet with the next buyer.*
- (ii) *If $n=1$ or $i = n$, the seller should allocate the good to the agent with valuation \hat{x}_n .*

Optimal Queue Lengths. We now turn to the optimal assignment of queue lengths across sellers, given the optimal trading protocol for after buyers arrive. Notice immediately that the planner's cutoff x^* is not only independent of the number of buyers, n , but also independent of λ , which governs the distribution over n . The reason is that the optimal stopping rule, on the margin, balances the costs and expected gains of additional meetings, conditional on the event that there *are* more buyers in the queue. The probability of this event, per se, is irrelevant: since the seller neither incurs additional costs nor forfeits the right to accept any previous offers if there are no more buyers in the queue, the probability distribution over the number of buyers remaining in the queue—and thus λ —does not affect the planner's choice of x^* .

Let $S(x^p, \lambda)$ denote the expected surplus generated at an individual seller whom the planner assigns a cutoff x^p and a queue length λ . In order to derive this function, it will be convenient to define

$$q_i(x; \lambda) = \frac{\lambda^i (1 - F(x))^i}{i!} e^{-\lambda(1-F(x))}. \quad (3)$$

In words, $q_i(x; \lambda)$ is the probability that a seller is visited by exactly i buyers, all of whom happen to draw a valuation greater than x (when all buyers' valuations are learned). In what follows, we will suppress the argument λ for notational convenience.

The net surplus generated at a particular seller is equal to the gains from trade, less the inspection costs. To derive the expected gains from trade at a seller with cutoff x^p and queue length λ , first suppose that n buyers arrive at this seller. There are three relevant cases. First, with probability $F(y)^n$ all n buyers draw valuation $x < y$, in which case there are no gains from trade. Second, with probability $F(x^p)^n - F(y)^n$, the maximum valuation among the n buyers is a value $x \in (y, x^p)$, in which case the gains from trade are $x - y$. Note that the conditional distribution of this maximal valuation x has density $[nF(x)^{n-1}f(x)] / [F(x^p)^n - F(y)^n]$. Finally, with probability $1 - F(x^p)^n$, at least one buyer has valuation $x \geq x^p$. In this case, the seller trades with the first buyer he encounters with a valuation that exceeds x^p ; this valuation is a random drawn from the conditional

distribution $f(x)/[1 - F(x^p)]$. Taking expectations across values of n , the gains from trade at a seller with cutoff x^p and queue length λ , in the absence of inspection costs, are

$$\begin{aligned} & \sum_{n=1}^{\infty} \frac{e^{-\lambda} \lambda^n}{n!} \left\{ \int_y^{x^p} (x-y) n F(x)^{n-1} f(x) dx + [1 - F(x^p)] \int_{x^p}^{\bar{x}} (x-y) \frac{f(x)}{1 - F(x^p)} dx \right\} \\ = & \int_y^{x^p} (x-y) \lambda q_0(x) f(x) dx + [1 - q_0(x^p)] \int_{x^p}^{\bar{x}} (x-y) \frac{f(x)}{1 - F(x^p)} dx. \end{aligned} \quad (4)$$

Now consider the expected inspection costs incurred by buyers at a seller with cutoff x^p and queue length λ . If a buyer arrives at a seller along with n other buyers, he will occupy the $(i+1)^{th}$ spot in line, for $i \in \{0, \dots, n\}$, with probability $1/(n+1)$. In this case, he will get to meet with the seller only when all buyers in spots $1, \dots, i$ draw $x < x^p$, which occurs with probability $F(x^p)^i$. Taking expectations over n implies that the ex ante probability that each buyer gets to meet with a seller with queue length λ , given a planner's cutoff of x^p , is

$$\sum_{n=0}^{\infty} \frac{e^{-\lambda} \lambda^n}{n!} \left\{ \sum_{i=0}^n F(x^p)^i \frac{1}{n+1} \right\} = \frac{1 - q_0(x^p)}{\lambda [1 - F(x^p)]}. \quad (5)$$

Note that this probability approaches one from below as x^p goes to \bar{x} . Moreover, since the expected number of buyers to arrive at this seller is λ , the total *expected* inspection cost incurred by all buyers is simply $([1 - q_0(x^p)] / [1 - F(x^p)]) k$.

Using the results above, the expected surplus generated by a seller with queue length λ and stopping rule x^p can be written as

$$S(x^p, \lambda) = \int_y^{x^p} (x-y) \lambda q_0(x) f(x) dx + \frac{1 - q_0(x^p)}{1 - F(x^p)} \left[\int_{x^p}^{\bar{x}} (x-y) f(x) dx - k \right]. \quad (6)$$

Given the optimality of $x^p = x^*$ for any λ , the objective of the planner is then to choose queue lengths at each seller, λ_j for $j \in [0, \theta_s]$, to maximize total surplus $\int_0^{\theta_s} S(x^*, \lambda_j) dj$ subject to the constraint that $\int_0^{\theta_s} \lambda_j dj = \theta_b$.

In the following lemma, we establish an important property of the surplus at a particular seller when the optimal trading rule is in place.

Lemma 2. $S(x^*, \lambda)$ is strictly concave in λ .

Two factors contribute to the concavity of $S(x^*, \lambda)$ with respect to λ . First, as is standard in models of directed search, the probability that a seller trades is concave in the queue length. This force alone typically implies that the planner assigns equal queue lengths across (homogeneous) sellers. However, in our environment there is an additional force, since the ex post gains from trade are also concave in the number of buyers that arrive: each additional buyer is less likely to meet

the seller and, conditional on meeting, is less likely to have a higher valuation than all previous buyers.

The Solution to the Planner’s Problem. Taken together, lemmas 1 and 2 are sufficient to establish that the planner maximizes total surplus by assigning equal queue lengths across all sellers, so that $\lambda_j = \Lambda$ for all j . The following proposition summarizes the planner’s solution.

Proposition 1. *The unique solution to the planner’s problem is to assign equal queue lengths Λ to each seller. After buyers arrive, the planner lets buyers inspect the good sequentially and assigns the good immediately whenever a buyer’s valuation exceeds x^* . When all valuations are below x^* and the queue is exhausted, the planner assigns the good to the agent with the highest valuation.*

4 The Decentralized Equilibrium

We now introduce a method of price determination that we call an “asking price mechanism.” We show that, when a seller uses this mechanism, buyers who inspect the good will truthfully reveal their valuations; inspections will continue until the first buyer in the queue draws a valuation above some (stationary) threshold; and, if no buyer draws a valuation above this threshold, the good will be allocated to the agent with the highest valuation. Given these features, the asking price mechanism is a natural candidate to implement the planner’s solution described in Proposition 1.

However, as we explain below, a seller’s choice of an asking price actually plays two roles: it determines the threshold conditional on a given number of buyers showing up (in expectation), but it also determines the expected number of buyers to begin with. Given these two separate roles, it is not obvious what asking prices sellers will choose in equilibrium, or whether their optimal choices will implement the constrained efficient allocation.

In this section, we characterize equilibrium asking prices and establish that the decentralized equilibrium indeed coincides with the solution to the planner’s problem. Then, in Section 5, we prove that the asking price mechanism is, in fact, a seller’s *optimal* mechanism; that is, there is no mechanism that provides a seller with a higher payoff, irrespective of the mechanisms posted by other sellers.

Asking Price Mechanism. An asking price mechanism, or APM, has two components: an asking price and a specific protocol that occurs after an arbitrary number of buyers arrive. More specifically, suppose a seller has posted an asking price a and n buyers arrive. The APM dictates that the seller will meet buyers one at a time, with each successive buyer being chosen randomly from the set of remaining buyers, until one of the buyers bids the asking price or all buyers are

met. During a meeting, a buyer incurs the inspection cost k , learns his valuation x , and submits a bid b . Importantly, when a buyer bids, he knows neither the number of other buyers at the seller, $n - 1$, nor his place in the queue.¹⁷

If the buyer bids $b \geq a$, his bid is accepted immediately and trade ensues; the asking price a is the price at which the seller commits to selling his good immediately (and subsequently stops meeting with other buyers). If $b < y$, then the bid is rejected and the seller moves to the next buyer. Finally, if $b \in [y, a)$, then the bid is neither rejected nor immediately accepted. Instead, the seller registers the bid and proceeds to meet the next buyer in line (if there is one). Again, the buyer incurs the cost k , learns her valuation x , and submits a bid b .

The process described above repeats itself until either the seller receives a bid $b \geq a$, or until he has met with all n buyers. In the latter case, he sells the good to the highest bidder at a price equal to the highest bid, as long as that bid exceeds his own valuation y . A seller who trades at price b receives a payoff equal to b , while a seller who does not trade receives payoff y . The payoff to a buyer who trades at price b is $x - b - k$. A buyer who meets with a seller but does not trade obtains a payoff $-k$. Finally, the payoff of a buyer who does not meet with a seller is equal to zero.

A Buyer's Strategy and Payoffs. Given an arbitrary distribution of asking prices posted by sellers, we now describe buyers' optimal search and bidding strategies. We work backwards, first deriving a buyer's optimal behavior and payoffs conditional on meeting a seller who posted an asking price a and attracted a queue λ . Then, given these payoffs, we derive buyers' optimal search behavior, which determines the queue length λ that corresponds to each asking price a .

To derive buyers' behavior and payoffs after arriving at a seller, it's helpful to note that the APM described above is equivalent to a mechanism in which buyers are randomly placed in line; each buyer is sequentially offered the opportunity to purchase the good at the asking price a , in which case trade occurs immediately; and, if no buyer chooses to pay the asking price, the good is allocated according to a first-price sealed-bid auction, where buyers are not told how many other buyers are also participating in the auction. As we will see, this alternative interpretation is helpful because it allows us to draw upon well-known results in the auction theory literature.¹⁸

We conjecture, and later confirm, that there exists a cutoff, which we denote x^a , such that a buyer with valuation x^a is exactly indifferent between paying the asking price and waiting to

¹⁷Note that the information available to the buyers should be viewed as a feature of the mechanism. Since we establish below that this mechanism is optimal, it follows that sellers have no incentive ex ante to design a mechanism in which buyers can observe either n or their place in the queue.

¹⁸This observation is also helpful because it implies that we can replace the first-price auction with any revenue-equivalent auction without changing any of the substantive results below. In most markets, we think the first-price auction most closely resembles the actual method of price determination. However, in Section 7, we explore the implications of using a second-price (ascending bid) auction instead, and argue that this alternative can help rationalize transaction prices above the asking price.

(perhaps) participate in an auction. Therefore, if a buyer draws valuation $x \geq x^a$, he will pay a and trade immediately. Otherwise, if $x < x^a$, he will decline and take his chances with the auction.

Assuming that all other buyers follow such a strategy, consider a buyer who has incurred the (sunk) cost k and discovered that his private valuation is x at a seller who has posted an asking price a and has an expected queue length λ . To decide whether to accept the asking price or not, the buyer needs to form beliefs about both the probability that the auction will take place and the number of other buyers that will be bidding. Note that when the buyer is asked to inspect, he updates his beliefs regarding both probabilities.¹⁹ In particular, conditional on the buyer meeting the seller, the probability that an auction will take place is

$$\frac{\lambda (1 - F(x^a))}{1 - q_0(x^a)} q_0(x^a). \quad (7)$$

To understand this expression, recall that the probability that a buyer gets to meet a seller is given by (5) and that an auction takes place if, and only if, none of the buyers in the queue draw a valuation above x^a , which happens with (ex ante) probability $q_0(x^a)$. Applying Bayes' rule then yields the expression in (7).

Similar logic can be used to calculate the distribution over the number of competitors that the buyer will face should an auction occur. The total number of buyers at the seller follows a Poisson distribution with mean λ . The auction will take place if all of them have a valuation below x^a , which happens with probability $F^n(x^a)$. Hence, conditional on there being an auction, the number of competitors equals n with probability

$$e^{-\lambda} \frac{\lambda^n F^n(x^a)}{n! q_0(x^a)} = e^{-\lambda F(x^a)} \frac{(\lambda F(x^a))^n}{n!}. \quad (8)$$

In Lemma 3, below, we use these probabilities to characterize the buyer's optimal bidding strategy and expected payoff should he choose not to pay the asking price, conditional on the queue length λ and the cutoff x^a being chosen by other buyers.

Lemma 3. *Consider buyers who arrive at a seller with queue length λ . If all buyers pay the asking price if, and only if, their valuation $x \geq x^a$, then the optimal bidding strategy of a buyer who draws valuation $x \in [y, x^a)$, conditional on reaching the auction, is*

$$\widehat{b}(x) = x - \frac{\int_y^x q_0(\tilde{x}) d\tilde{x}}{q_0(x)} < x, \quad (9)$$

¹⁹In other words, the very act of meeting the seller and inspecting the good is informative, since inspecting the good requires that no previous buyer drew a valuation above x^a . In particular, after inspecting the good, a buyer's posterior belief that many buyers arrived at the seller falls, and he believes it is more likely that he will be competing against relatively few other buyers.

and this buyer's expected payoff from the auction is

$$u(x) = \frac{\lambda(1 - F(x^a))}{1 - q_0(x^a)} \int_y^x q_0(\tilde{x}) d\tilde{x}. \quad (10)$$

Since $q_0(x)$ is, in fact, a function of λ , so too is $\widehat{b}(x)$, while $u(x)$ is actually a function of *both* λ and x^a . Though we have suppressed these arguments for notational convenience, it should be understood that, for example, the buyer's expected utility from entering the auction depends on both the expected number of buyers at the seller and the threshold strategy that they are playing.

Importantly, note that $u(x)$ is strictly increasing in x , which confirms our conjecture that buyers follow a threshold strategy. Moreover, the threshold x^a must satisfy $u(x^a) = x^a - a$, or

$$a = x^a - \frac{\lambda(1 - F(x^a))}{1 - q_0(x^a)} \int_y^{x^a} q_0(x) dx. \quad (11)$$

In the Appendix, we confirm that $\frac{da}{dx^a} > 0$, so that the relationship between a and x^a is one-to-one. Hence, given any a and λ , the buyer's optimal bidding function is completely characterized by

$$b(x) = \begin{cases} 0 & \text{if } x < y \\ \widehat{b}(x) & \text{if } y \leq x < x^a \\ a & \text{if } x^a \leq x, \end{cases} \quad (12)$$

where $\widehat{b}(x)$ is given by (9) and x^a is determined by (11).²⁰

Given a buyer's optimal behavior conditional on meeting the seller, we can calculate the ex ante expected utility that a buyer receives from visiting a seller who has posted an asking price a and attracted a queue length λ ,

$$U(a, \lambda) = \frac{1 - q_0(x^a)}{\lambda(1 - F(x^a))} \left[\int_y^{x^a} u(x) dF(x) + \int_{x^a}^{\bar{x}} (x - a) dF(x) - k \right], \quad (13)$$

where, in a slight abuse of notation, $x^a \equiv x^a(a, \lambda)$ is the implicit function defined in (11).

Given $U(a, \lambda)$, the optimal search behavior of buyers is straightforward: given the set of asking prices that have been posted, along with the search decisions of other buyers, an individual buyer should visit a seller (or mix between sellers) that maximizes $U(a, \lambda)$. More formally, for an arbitrary distribution of posted asking prices, let \bar{U} denote the highest level of utility that buyers can obtain; as is common in this literature, we will refer to \bar{U} as the "market utility." Then, for any

²⁰Notice that $\lim_{x \rightarrow x^a} \widehat{b}(x) < a$, which should be expected. Otherwise, for buyers with valuation x arbitrarily smaller than x^a , an arbitrarily small increase in their bid would yield a discrete increase in the probability of trading, and hence a discrete increase in their expected payoff.

asking price a that has been posted, the queue length $\lambda(a) \geq 0$ must satisfy

$$U(a, \lambda(a)) \leq \bar{U}, \text{ with equality if } \lambda(a) > 0. \quad (14)$$

According to equation (14), buyers will adjust their search behavior in such a way to make themselves indifferent between any seller that they visit with positive probability.

A Seller's Strategy and Payoffs. Given the optimal behavior of buyers, we can now characterize the profit-maximizing asking price set by sellers. As a first step, we use the results above to derive the expected revenue of a seller who has set an asking price a and attracted queue length λ :

$$R(a, \lambda) = q_0(y)y + \int_y^{x^a} \hat{b}(x) dq_0(x) + (1 - q_0(x^a))a. \quad (15)$$

Again, note that $x^a \equiv x^a(a, \lambda)$ denotes the optimal cutoff for buyers characterized in (11) and $\hat{b}(x)$ denotes the optimal bidding function characterized in (9). This expression captures the three possible outcomes for a seller: no buyers arrive with valuation $x > y$, in which case the seller consumes his own good; no buyers arrive with valuation $x > x^a$, but at least one buyer has valuation $x > y$, in which case the seller accepts the bid placed by the buyer with the highest valuation; or at least one buyer has a valuation $x \geq x^a$, in which case the seller receives a payoff a .

Sellers want to maximize expected revenue, taking into account that their choice of the asking price a will affect the expected number of buyers that will visit them, λ . In particular, in equilibrium the relationship between a and λ will be determined by the equality

$$U(a, \lambda) = \bar{U}. \quad (16)$$

The implicit function defined in (16) is akin to a typical demand function: for a given level of market utility, it defines a downward sloping relationship between the asking price a seller sets and the number of customers he receives (in expectation). The seller's problem can thus be interpreted as a choice over both the asking price and the queue length in order to maximize revenue, subject to (16). The corresponding Lagrangian can be written²¹

$$\mathcal{L}(a, \lambda, \mu) = R(a, \lambda) + \mu [U(a, \lambda) - \bar{U}]. \quad (17)$$

²¹So long as \bar{U} is sufficiently small, the solution will be interior and hence the first-order conditions of the Lagrangian are necessary. Sufficiency follows from the fact that the unique solution coincides with the planner's allocation, as we prove below.

Equilibrium. In general, an equilibrium is a distribution $G(a, \lambda)$ and a market utility \bar{U} such that (i) every pair in the support of G is a solution to (17), given \bar{U} ; and (ii) aggregating queue lengths across all sellers, given the distribution G and the mass of sellers θ_s , yields the total measure of buyers, θ_b . However, as we establish in the proposition below, in fact there is a unique solution to (17), and hence G is degenerate. Furthermore, this solution coincides with the planner's solution, i.e., the equilibrium is efficient.

Proposition 2. *Given assumption (1), the decentralized equilibrium is characterized by*

$$a = a^* \equiv x^* - \frac{\lambda(1 - F(x^*))}{1 - q_0(x^*)} \int_y^{x^*} q_0(x) dx, \quad (18)$$

$x^a = x^*$ and $\lambda = \Lambda$ at all sellers, with buyers receiving market utility $\bar{U}^* \equiv U(a^*, \Lambda)$. Hence, the decentralized equilibrium coincides with the solution to the planner's problem.

Asking Prices and Constrained Efficiency. Before proceeding, we offer a brief discussion of the result in Proposition 2. Notice immediately that the asking price mechanism we describe has all the right ingredients to implement the efficient allocation at each seller: it elicits buyers' private valuations sequentially, it implements a stationary cutoff rule, and it allows for the seller to trade with any buyer that has inspected the good (i.e., it allows for perfect recall).

What is less clear is whether the asking price that sellers choose in equilibrium will implement the *efficient* cutoff, x^* . The reason is that the choice of a is affecting two margins: the expected number of buyers who arrive at the seller, λ , and the stopping rule after buyers arrive, x^a . One way to understand these two margins more clearly is to use the relationship

$$R(a, \lambda) = S(x^a(a, \lambda), \lambda) - \lambda U(a, \lambda)$$

to rewrite the Lagrangian (17), where $x^a(a, \lambda)$ is defined in (11). Taking first order conditions and substituting the constraint, (16), we get that profit maximization requires

$$\frac{\partial \lambda}{\partial a} \left[\frac{\partial S}{\partial \lambda} - \bar{U} \right] + \frac{\partial S}{\partial x^a} \frac{dx^a}{da} = 0. \quad (19)$$

The first term in (19) represents the seller's marginal revenue from increasing a , holding the threshold x^a constant. In particular, note that the marginal revenue from an additional buyer, in expectation, is equal to the additional surplus this buyer creates, $\partial S / \partial \lambda$, less the "cost" of acquiring this buyer, \bar{U} . The second term represents the seller's marginal revenue from increasing a , holding the queue length λ constant.

Profit maximization, of course, just requires that the *sum* of the two terms in (19) is equal to

zero. Constrained efficiency, on the other hand, requires that *each* of the two terms in (19) is equal to zero: implementing the solution to the planner’s problem requires both maximizing the surplus after buyers arrive and inducing the right number of buyers to arrive in the first place. The former requirement equates to ensuring that $\frac{\partial S}{\partial x^a} = 0$, so that the asking price implements the stopping rule $x^a = x^*$. The latter demands that, in equilibrium, $\frac{\partial S}{\partial \lambda} = \bar{U}$; this is a standard condition for the ex ante efficient allocation of buyers across sellers, as it implies that each buyer receive (in expectation) his marginal contribution to the match.²²

A priori, there is no reason to think that one value of a will ensure that both of these conditions are satisfied. Indeed, given that one instrument is affecting two margins, one could easily imagine a seller being forced to trade off ex post efficiency—so that $\partial S/\partial x^a \neq 0$ —in order to influence ex ante demand.²³ Clearly, the relationship between a , x^a , and λ has to be just right in order to ensure that both conditions are satisfied with a single choice of a .

A quick glance at equation (11), along with (7), reveals that the *information structure* is crucial in determining this relationship between a , x^a , and λ . In particular, this relationship depends on the probability that a buyer wins the good given only the information contained in the fact that he has met with the seller. This turns out to be exactly the right amount of information to reveal to the buyer in order to ensure that such a simple, stationary mechanism can implement the optimal stopping rule. To see this, suppose we replace our asking price mechanism with a standard (sealed-bid) auction. In this case, buyers have *no information* about the valuations of other buyers, and one can show that too many buyers ultimately inspect the good. Now suppose that we allow each buyer to observe the bids of those who have inspected the good before him, as in Bulow and Klemperer (2009). Then, in the simple sequential mechanism they study, each buyer has an incentive to place a bid that inefficiently preempts further participation. Therefore, if buyers have *too much information*, then too few buyers will ultimately inspect the good.²⁴

With the equilibrium asking price, a buyer who is about to inspect the good is able to infer *just enough*: namely, that no other buyer has had a valuation high enough to bid the asking price, making it worthwhile to pay the inspection cost.²⁵ However, he is not able to infer more, which eliminates the strategic motive of previous bidders to pre-empt entry. In this sense, the equilibrium asking price is essentially a “jump-bid” that does pre-empt entry, but precisely when it is efficient

²²See, e.g., Mortensen (1982), Hosios (1990), and Moen (1997).

²³If the seller had two instruments at his disposal—say, an asking price to implement a stopping rule and a fee (or subsidy) to transfer rents at will—clearly the seller would choose an asking price to implement x^* and a fee or subsidy to independently influence the queue length λ . What’s interesting here is that such fees or subsidies are not necessary.

²⁴This is precisely why Crémer et al. (2009) find that the optimal mechanism must include asking prices and fees that vary with each buyer in the queue, which can be used to correct the distortions in the simple mechanism of Bulow and Klemperer (2009).

²⁵In a related environment with two bidders, Pansc (2013) also finds that partial disclosure is optimal for the seller. Also see McAdams (2015), who studies optimal disclosure in an environment where buyers choose when to enter a mechanism.

to do so. Moreover, the size of the jump bid is such that each buyer, from an ex ante point of view, receives exactly his expected contribution to the total surplus, which ensures that the socially optimal number of buyers visit each seller to begin with.²⁶

5 General Mechanisms

Proposition 2 characterizes the equilibrium that arises when sellers compete by posting asking prices, and establishes that the equilibrium coincides with the solution to the social planner's problem. However, it remains to be shown that sellers would in fact *choose* to utilize the asking price mechanism if we expanded their choice set to include more general mechanisms.

In this section, we establish several important results. First, even when sellers are free to post arbitrary mechanisms, all sellers posting the optimal asking price mechanism described in Proposition 2 remains an equilibrium. Moreover, while other equilibria can arise, all of these equilibria are payoff-equivalent to the equilibrium with optimal asking prices; in particular, there is no equilibrium in which sellers earn higher payoffs than they do in the equilibrium with optimal asking prices. Finally, we show that *any* mechanism that emerges as an equilibrium in this environment will resemble the asking price mechanism along several important dimensions: any equilibrium mechanism will require that the seller meets with buyers sequentially, that meetings continue until a buyer draws a valuation x^* , and that the (expected) payment by a buyer with valuation $x \geq x^*$ is equal to a^* . Hence, though we cannot rule out potentially complicated mechanisms that satisfy these properties, the fact that asking prices are both simple and commonly observed in the real world suggests that they are a robust and compelling way to deal with the frictions in our environment.

Mechanisms. Consider a seller who receives n buyers. In general, a mechanism is going to specify an extensive form game that determines, for each $i \in \{1, \dots, n\}$,

1. a probability $\phi_{i,n} : \mathcal{X}^{i-1} \rightarrow [0, 1]$ that the i^{th} buyer inspects the good conditional on the messages $(\tilde{x}_1, \dots, \tilde{x}_{i-1}) \in \mathcal{X}^{i-1}$ reported by previous buyers, where $\mathcal{X} = \{\emptyset\} \cup [\underline{x}, \bar{x}]$ is the space of messages available to buyers, $\tilde{x} = \emptyset \in \mathcal{X}$ denotes the event that buyer i did not inspect the good, and $\mathcal{X}^0 = \{\emptyset\}$ by convention;

²⁶To see that the information structure alone is insufficient to guarantee that a simple asking price is the optimal mechanism, suppose the number of buyers at each seller is exogenous. In this environment, which resembles Milgrom (2004, page 232), a seller who has access to only a simple asking price mechanism will again face a trade-off between revenue maximization and efficiency, as in Bulow and Klemperer (2009); an unrestricted seller would optimally impose meeting fees on each buyer who inspects the good. Competition among sellers eliminates these fees.

2. a disclosure rule $\sigma_{i,n} : \mathcal{X}^{i-1} \rightarrow \Sigma$ that specifies the signal that the i^{th} buyer receives conditional on the vector of reports from previous buyers, $(\tilde{x}_1, \dots, \tilde{x}_{i-1}) \in \mathcal{X}^{i-1}$, where Σ is the space of signals that can be disclosed;²⁷
3. a decision rule $\delta : \Sigma \rightarrow [0, 1]$ that specifies the probability that a buyer will inspect the good conditional on receiving the signal $\sigma \in \Sigma$;
4. a report $\tilde{x} : \Sigma \times \mathcal{X} \rightarrow \mathcal{X}$ that the buyer sends to the seller conditional on receiving a signal $\sigma \in \Sigma$ and either not inspecting or discovering a valuation $x \in [\underline{x}, \bar{x}]$;

along with

5. an allocation rule $\alpha_n : \mathcal{X}^n \rightarrow \{0, 1, \dots, n\}$ which specifies that the good is allocated to either the i^{th} buyer in the queue, for $i \in \{1, \dots, n\}$, or the seller ($i = 0$), conditional on the set of messages $(\tilde{x}_1, \dots, \tilde{x}_n)$;
6. transfers $\tau_n : \mathcal{X}^n \rightarrow \mathbb{R}^n$ which specifies the transfers to/from each of the n buyers, conditional on the set of messages $(\tilde{x}_1, \dots, \tilde{x}_n)$;

subject to standard feasibility and aggregate consistency constraints.

We will restrict attention to the set of all mechanisms \mathcal{M} that satisfy individual rationality and incentive compatibility. In particular, for every $m \in \mathcal{M}$, a buyer's expected payoff when instructed to inspect the good is non-negative, given the information available to him, and truthfully reporting his valuation x (at least weakly) dominates reporting any $x' \neq x$.²⁸ In very similar environments, Crémer et al. (2009) and Pancs (2013) show that these two additional restrictions—namely, that buyers are both *obedient* when instructed to inspect and *truthful* in reporting their type — are essentially without loss of generality.²⁹

Given these implicit restrictions, a mechanism $m \in \mathcal{M}$ can simply be summarized by the inspection probabilities and rules for disclosure, allocations, and transfers described above. Note that the set \mathcal{M} includes a mechanism that implements our equilibrium asking price mechanism; we denote this mechanism by m_a^* . The set \mathcal{M} also includes mechanisms that implement a cutoff

²⁷The set of potential signals is quite vast. For one, the seller could disclose the buyer's exact place in line, some information about his place in line (i.e., whether he is among the first n buyers) or no information about his place in line. Similarly, the seller could disclose all of the valuations reported by previous buyers, no information about previous buyers, or various statistics summarizing the reports that have been received, such as the maximum valuation reported or whether any buyers had reported a valuation above some threshold.

²⁸We are also implicitly assuming *truthful disclosure*, i.e., that the seller does not report false information to the buyers.

²⁹There are, however, two implicit restrictions on the mechanism space which are worth noting, though both are standard in the literature on competing mechanisms (see, e.g., Eeckhout and Kircher, 2010). First, we do not allow mechanisms to condition on buyers' ex ante identities; identical buyers must be treated symmetrically. Second, we do not allow mechanisms to condition on the trading mechanisms posted by other sellers.

rule associated with other asking prices, as well as completely different, potentially much more complicated, mechanisms.

Payoffs. For a given mechanism m , expected revenue can be calculated in the usual way, taking expectations across the number n and the valuations of other buyers. Expected utility can be calculated in a similar manner, taking expectations across the number n , a buyer's (random) place in line, and the valuations reported by other buyers. We denote the ex ante expected payoff of a seller who posts a mechanism $m \in \mathcal{M}$ and attracts a queue λ by $\mathbf{R}(m, \lambda)$, while $\mathbf{U}(m, \lambda)$ represents the expected payoff of each buyer in his queue. The total payoffs (net of y) cannot exceed the amount of surplus $\mathbf{S}(m, \lambda)$ generated by the seller's chosen mechanism, which in turn cannot exceed the surplus created by the mechanism that implements the planner's solution, $\mathbf{S}^*(\lambda) \equiv S(x^*, \lambda)$. That is,

$$\mathbf{R}(m, \lambda) + \lambda \mathbf{U}(m, \lambda) - y \leq \mathbf{S}(m, \lambda) \leq \mathbf{S}^*(\lambda) \quad (20)$$

for all m and λ . Clearly, Pareto optimality requires that the surplus be divided between the seller and the buyers, so we restrict attention to mechanisms that satisfy the first condition in (20) with equality. If the second condition in (20) also holds with equality, i.e., the mechanism creates the same amount of surplus as the planner's solution, we will call the mechanism *surplus-maximizing*.

Equilibrium. An equilibrium in this more general environment is a distribution of mechanisms $m \in \mathcal{M}$ and queue lengths $\lambda \in \mathbb{R}_+$ across sellers, along with a market utility \bar{U} , such that (i) given \bar{U} , each pair (m, λ) maximizes profits $\mathbf{R}(m, \lambda)$ subject to the constraint $\mathbf{U}(m, \lambda) = \bar{U}$; and (ii) aggregating queue lengths across all sellers yields the total measure of buyers, θ_b . Given this definition, we now establish that a mechanism $m \in \mathcal{M}$ is an optimal strategy if, and only if, it creates the same surplus and the same expected payoffs as the asking price mechanism described in the previous section, where the asking price a is set to implement the cutoff x^* .

Proposition 3. *Take any candidate equilibrium with market utility $0 < \bar{U} < \int_y^{\bar{x}} (x - y)f(x)dx - k$. Let m_a^* denote the asking price mechanism that implements the cutoff x^* , and let λ_a satisfy $\mathbf{U}(m_a^*, \lambda_a) = \bar{U}$. A mechanism $m \in \mathcal{M}$, which attracts a queue length λ , maximizes a seller's expected profits if, and only if,*

- (i) $\mathbf{S}(m, \lambda) = \mathbf{S}^*(\lambda)$;
- (ii) $\mathbf{R}(m, \lambda) = \mathbf{R}(m_a^*, \lambda_a)$; and
- (iii) $\lambda = \lambda_a$.

The intuition behind Proposition 3 is illustrated in Figure 1. Consider a candidate equilibrium with market utility \bar{U} in which a seller posts a mechanism m_1 and receives a queue λ_1 satisfying $\bar{U} = \mathbf{U}(m_1, \lambda_1)$, yielding expected profits $\mathbf{R}(m_1, \lambda_1) - y = \mathbf{S}(m_1, \lambda_1) - \lambda_1 \bar{U}$.

INSERT FIGURE 1 HERE

The first result is that m_1 must be surplus-maximizing. To see why, suppose it is not; that is, suppose $\mathbf{S}(m_1, \lambda_1) < \mathbf{S}^*(\lambda_1)$, corresponding to point 1 in Figure 1. This seller's expected profits correspond to the intersection of the vertical axis with the line through point 1 that has slope \bar{U} . One can see immediately that this cannot be consistent with equilibrium behavior. For example, the seller could deviate to a surplus-maximizing mechanism m_2 that attracts the same queue length λ_1 but yields a larger surplus $\mathbf{S}(m_2, \lambda_1) = \mathbf{S}^*(\lambda_1)$, corresponding to point 2 in the figure.³⁰ Since this deviation increases the size of the surplus, while holding constant the market utility received by the buyers, it strictly increases the seller's profits, i.e., $\mathbf{R}(m_2, \lambda_1) > \mathbf{R}(m_1, \lambda_1)$.

In general, a seller can obtain an even higher payoff. As the figure shows, profits are maximized at point 3. That is, not only must any equilibrium mechanism lie on the surplus-maximizing frontier $\mathbf{S}^*(\lambda)$, it must also induce a queue length λ_3 such that³¹

$$\left. \frac{d\mathbf{S}^*(\lambda)}{d\lambda} \right|_{\lambda=\lambda_3} = \bar{U}. \quad (21)$$

Equation (21) is a typical requirement for profit-maximizing behavior: the left-hand side is the marginal benefit of attracting a longer queue length, while the right-hand side is the marginal cost.

Importantly, the asking price mechanism that implements x^* satisfies this condition, as we have demonstrated in the previous section. Hence, for any market utility \bar{U} , a seller (weakly) maximizes his revenue if he posts a surplus-maximizing asking price mechanism. In other words, irrespective of the behavior of other sellers, it is always optimal for an individual seller to post an asking price mechanism that implements x^* . Note that—out of equilibrium—the asking price that achieves this may not be equal to a^* , since that requires $\bar{U} = \bar{U}^*$.

Finally, any profit-maximizing mechanism must attract a queue length equal to the queue length at a seller who posts m_a^* . Intuitively, since the queue length λ_a equates the marginal benefit of attracting more buyers with the more marginal cost, any other queue length would yield the seller strictly lower profits. Therefore, in equilibrium, all sellers must attract the same queue length, so that $\lambda = \Lambda$. The following corollary is an immediate consequence of the results in Proposition 3.

Corollary 1. *All sellers posting the optimal asking price mechanism m_a^* and attracting a queue Λ is an equilibrium within the mechanism space \mathcal{M} .*

Therefore, even when sellers are free to post arbitrary mechanisms, posting an asking price mechanism with $a = a^*$ is consistent with equilibrium behavior. Now, it is true that other mechanisms could also be utilized in equilibrium, but Proposition 3 implies that any such mechanism

³⁰Such a deviation could be achieved by setting an asking price that implements the cutoff x^* , along with a fee (or subsidy) that ensures the expected payoff to buyers—and hence λ_1 —was unchanged.

³¹Recall that $\mathbf{S}^*(\lambda) = S(x^*, \lambda)$ is strictly concave in λ .

will be similar to the asking price mechanism along several important dimensions. To start, since any equilibrium mechanism must be surplus-maximizing, and thus implement an allocation that coincides with the unique solution to the planner’s problem, the mechanism must feature sequential meetings between the seller and the buyers, with a stopping rule x^* that depends explicitly on the realization of buyers’ valuations. Moreover, the mechanism must also allocate the good to the agent with the highest valuation in the event that no agent draws a valuation $x \geq x^*$.

Finally, since the ex ante probability that each buyer gets to meet with the seller must be equal in any equilibrium, and any mechanism that arises in equilibrium must also be payoff-equivalent to the equilibrium with optimal asking prices, it follows that the expected payment by buyers with valuation $x \in [x^*, \bar{x}]$ must equal the optimal asking price. Therefore, even when sellers utilize an alternative mechanism in equilibrium, the expected transfer from a buyer who “stops” the sequential inspection process will, indeed, equal a^* . The following corollary summarizes.

Corollary 2. *Any equilibrium strategy $m \in \mathcal{M}$ must specify that the seller meet with buyers sequentially; that these meetings stop if, and only if, either the buyer draws a valuation $x \geq x^*$ or the end of the queue is reached; and that the expected payment for a buyer who draws valuation $x \geq x^*$ is equal to a^* .*

6 Positive Implications

In this section, we flesh out some of the model’s implications for a variety of observable outcomes, including the level of asking prices set by the sellers, the number of buyers who inspect the good at each seller, and the ultimate transaction price. We study how these variables change with features of the economic environment, such as the ratio of buyers to sellers, the degree of ex ante uncertainty in buyers’ valuations, and the costs of inspecting the good.

Prices and Allocations. Figure 2 below plots a typical CDF of transaction prices, where we set $b = 0$ to represent sellers that do not trade.³² Notice that a fraction $q_0(y) = e^{-\Lambda[1-F(y)]}$ of sellers do not trade, either because no buyers arrive, which occurs with probability $q_0(\underline{x}) = e^{-\Lambda}$, or because $n \geq 1$ buyers arrive but their valuations do not exceed the seller’s valuation y , which occurs with probability $q_0(y) - q_0(\underline{x})$. A fraction $q_0(x^*) - q_0(y)$ of sellers ultimately accept a bid b that is strictly less than the asking price. Letting $\hat{x}(b) = \hat{b}^{-1}(x)$, where $\hat{b}(x)$ is defined in (9), the (cumulative) distribution of winning bids $b \in [y, \hat{b}(x^*)]$ is simply $q_0(\hat{x}(b))$. Finally, a fraction $1 - q_0(x^*)$ of sellers trade at the asking price.

³²For the sake of illustration, all numerical examples below have been generated with the assumption that x is uniformly distributed, though all of the results are true for arbitrary distributions.

INSERT FIGURE 2 HERE

As we discussed above, notice that there is a mass point of transactions that occur at a^* and a gap in the distribution between $\widehat{b}(x^*)$ and a^* . Intuitively, it cannot be optimal for a buyer to offer a price arbitrarily close to the asking price; such a strategy would be dominated by offering $b = a^*$, which would provide a discrete increase in the probability of trade, at the cost of an arbitrarily small increase in the terms of trade.

Comparative Statics. Figures 3 and 4 below illustrate how equilibrium prices are affected by changes in the ratio of buyers to sellers (Λ) and changes in the inspection cost (k). An increase in Λ causes a decrease in the fraction of sellers who do not trade and an increase in the fraction of sellers who trade at the asking price. Though x^* is independent of Λ , notice that a^* is not; it is easy to verify that a^* is an increasing function of Λ . More generally, the distribution of prices under a larger Λ first-order stochastically dominates the distribution of prices under a smaller Λ . Hence, as in standard models of competitive search, an increase in the buyer-seller ratio leads to higher prices in equilibrium. Notice, however, that the degree of dispersion in prices will be non-monotonic in Λ : though price dispersion exists for intermediate values of Λ , the equilibrium price distribution becomes degenerate at $b = y$ ($b = x^*$) as Λ converges to zero (infinity).

Alternatively, as the inspection cost k decreases, both the asking price a^* and the cut-off x^* increase. However, the buyers' bidding function $\widehat{b}(x)$ is unaffected, and hence the lower tail of the equilibrium price distribution is unaffected. As a result, a decrease in k leads to fewer transactions at the asking price. Finally, as k converges to zero, the optimal x^* converges to \bar{x} and the pricing mechanism converges to a standard first-price auction.

INSERT FIGURES 3 and 4 HERE.

Information and Uncertainty. One might also be interested in the relationship between the ex ante dispersion in buyers' valuations, asking prices, and the ultimate transaction prices. For example, suppose a new technology (e.g., the Internet) replaces an old technology (e.g., the newspaper), allowing buyers to learn more information about each seller's good before choosing a seller to visit. Given this information, suppose now that a buyer can identify a fraction η of goods that he would prefer, and a fraction $1 - \eta$ of goods that he would not. Formally, a good that is preferred will yield a valuation $x \in [x', \bar{x}]$, while a good that is not will yield the buyer a valuation $x \in [\underline{x}, x']$, where $\underline{x} < x' \leq y < \bar{x}$. Whether or not a good is preferred is again i.i.d. across goods for each buyer.

One can easily show that buyers only visit preferred sellers and that the resulting equilibrium is very similar to what we characterize in Proposition 2, with the exception that the distribution F with support $[\underline{x}, \bar{x}]$ is replaced by the truncated distribution F' with support $[x', \bar{x}]$. Figure 5 below illustrates the main effects of this technological improvement.

INSERT FIGURE 5 HERE

First, notice that fewer sellers don't trade, even though equilibrium queue lengths remain $\lambda = \Lambda$ at each seller. Intuitively, though the fraction of sellers who are visited by zero buyers remains constant, the truncated distribution implies that it is less likely for a seller to be visited by $n \geq 1$ buyers who all have a valuation strictly less than y . Second, notice that prices increase. This occurs for several reasons. For one, sellers set higher asking prices; on the margin, the expected gain from meeting with an additional buyer is larger since the truncated distribution F' first-order stochastically dominates the original distribution F . Moreover, since *other* buyers are more likely to draw a high valuation, there is more competition amongst buyers. This puts upward pressure on the bidding function, further increasing transaction prices. Given these two forces, clearly sellers' profits increase. Buyers, on the other hand, are more likely to trade, but at less favorable prices.

7 Assumptions and Extensions

In this section, we discuss several of our key assumptions, along with a few potentially interesting extensions of our basic framework.

Transactions Above the Asking Price. In the equilibrium characterized in section 4, no transaction takes place at a price that exceeds the asking price. While we believe this prediction to be adequate for certain markets, it is perhaps less desirable for the analysis of other markets, such as housing. It is therefore important to emphasize that our model can easily explain such transaction prices.³³ To see this, note that one can interpret our asking price mechanism as a two-stage process in which the seller first sequentially offers the good to each buyer at a price a^* and then organizes a first-price auction if no buyer accepts this offer. Given proposition 3 and standard revenue-equivalence results, an alternative, optimal mechanism would be to replace the first-price auction with a second-price auction in the second stage of the game.

Note that such a mechanism has a natural interpretation in the context of a housing market. It corresponds to a scenario in which a seller, after getting a number of offers which are all below the asking price, contacts the buyers again, informs them of the competing bids, and asks them whether they would like to increase their offer. In that case, a "bidding war" ensues until a single buyer remains, implementing the outcome of a second-price auction.

While this mechanism yields the same *expected* payoffs as our (first-price) asking price mechanism, the distributions of *realized* transaction prices will differ. Figure 6 shows a typical CDF of transaction prices, where we again use a price equal to 0 to represent sellers that do not trade.

³³We would like to thank Rob Shimer for pointing out this feature of our model.

As buyers bid their valuation in a second-price auction, a transaction price above the asking price arises when at least two buyers have a valuation above a but below x^a (or otherwise one of them would end the game by paying the asking price in the first stage). The probability of this event is strictly positive because $a < x^a$. The following lemma presents an explicit expression.

Lemma 4. *Suppose all sellers post a two-stage mechanism consisting of an asking price in the first stage, followed by a second-price auction. The probability that a transaction takes place at a price exceeding the asking price then equals*

$$e^{-\lambda(1-F(x^a))} - e^{-\lambda(1-F(a))} - \lambda e^{-\lambda(1-F(a))} (F(x^a) - F(a)) > 0.$$

Hence, this interpretation yields a micro-founded model in which a positive mass of transactions occur at the posted asking price, while other transactions occur both below and above the asking price.

INSERT FIGURE 6 HERE

Commitment. Throughout our analysis, we also assume that sellers can commit to carrying out the mechanism that they post. In particular, when a seller posts an asking price, we assume that he commits to trading with the first buyer who offers to pay this price, even though ex post he would prefer to renege and meet with all buyers.

Though this assumption is strong, we believe there are a number of ways to enforce this type of behavior. Some are technological: for example, online auction sites like eBay and Amazon allow sellers to pre-commit to an asking price (what they call “Buy-It-Now” or “Take-It” prices, respectively), in which the auction immediately stops once this price offer is received. In other cases, there exist institutions that make it costly to renege on an asking price. For example, as Stacey (2012) points out, real estate agents in the housing market can serve as commitment devices. For one, sellers are typically required to pay their real estate agent a commission if they receive a *bona fide* offer at the asking price, whether or not the offer is accepted. Even without this contractual clause, reputation concerns can help enforce commitment: if a homeowner repeatedly turns down buyers who offer the posted asking price, he will not only discourage brokers from listing his property, but he may also discourage other buyers from making offers in the future.

For all of these reasons, we think that the assumption of full commitment is a reasonable approximation of the way goods are sold in certain markets. Of course, there are other markets in which sellers may not be able to commit to such a device; extending our framework to allow for limited commitment, or even no commitment (as in Kim and Kircher, 2015), could potentially allow our model to capture these features as well. This extension is left for future work.³⁴

³⁴A stylized but particularly tractable approach would be to assume that, after the arrival of the buyers, the seller

Endogenous Inspection. Throughout the text we assumed that buyers inspect the good and learn their valuation before submitting a bid. One interpretation of this assumption is that it is a technological constraint: a buyer simply must go and meet with the seller in order to make an offer (say, he needs to sign certain documents), and this process is costly.

However, for many applications it may be more appropriate to treat the decision to inspect the good as endogenous. In such an environment, if the inspection cost k becomes too large, there may exist states of the world in which the buyer (or the planner) prefers to forgo inspection and place a bid (or trade) without knowing the valuation. The following lemma derives a condition on k to ensure that this is never the case. That is, under the condition below, inspection before submitting a bid or trading is optimal both for the planner and for the buyers in the decentralized market.

Lemma 5. *The planner always instructs buyers to inspect the good upon meeting a seller and, in the decentralized equilibrium, buyers always choose to inspect the good before submitting a bid if and only if*

$$k < \int_x^y (y - x) f(x) dx. \quad (22)$$

Hence, the analysis in Sections 3 and 4 is consistent with an environment in which the decision to inspect the good is endogenous, but k is sufficiently small to satisfy (22). In words, this inequality implies that inspection is always optimal as long as the cost of inspecting is smaller than the costs associated with inefficient trade, which occurs when the seller values the good more than the buyer who receives it. Before proceeding, we highlight two important points regarding (22). First, inspection will, in general, almost always remain an optimal strategy for buyers in large regions of the parameter space that do not satisfy this condition. Second, for most of the goods we have in mind (e.g., a house or a car), the assumption that the inspection cost k is small relative to the potential gains (or losses) from trade seems to be appropriate.

Heterogeneous Goods. We now consider the case where sellers possess different types of goods, where these differences are verifiable ex ante (i.e., before inspecting). This case is of interest for at least two reasons. First, it is an obvious extension; in the housing market, for example, there are one-bedroom apartments and four-bedroom houses, and these differences are known before a potential buyer chooses which seller to visit. Second, this extension highlights the type of questions that can be considered in our market setting—where there are many sellers—but would be more difficult (if not impossible) to analyze in a closely related set of models that assume only a single seller, such as Crémer et al. (2009).

can renege on the asking price at a certain cost or in certain states of the world. This would not only allow our model to accommodate transaction prices above the asking price, but it would also create a natural intermediate case between our framework and the model by Albrecht et al. (2015).

To this end, suppose that a fraction ϕ_i of sellers possess a good of type $i \in \{1, 2\}$, with $\phi_1 + \phi_2 = 1$.³⁵ Sellers of type i have a valuation y_i for their own good, while buyers draw valuations from a distribution $F_i(x)$ after inspecting the good of a seller of type $i \in \{1, 2\}$. In the following lemma, we establish that our main results are robust to the introduction of this type of heterogeneity. That is, sellers will still choose to use an asking price mechanism in equilibrium, and the corresponding equilibrium allocation will coincide with the solution to the planner’s problem.

Lemma 6. *In a market with two different goods, all sellers using the asking price mechanism is an equilibrium and this equilibrium is efficient.*

In the corresponding equilibrium, submarkets form for each type of good, with an asking price a_i^* and a queue of buyers λ_i^* , implementing a cutoff type x_i^* .³⁶ However, in general, whether or not a_1 is greater or less than a_2 will depend on a number of factors.

To start, suppose $F_1(x) = F_2(x)$ and consider only the effect of $y_2 > y_1$. While this has no effect on x^* —which is evident from equation (2)—it has opposing effects on the asking price. On the one hand, a larger value of y implies that buyers must place higher bids to acquire the good, which places upward pressure on the asking price of type 2 sellers. On the other hand, however, a larger value of y also lowers the potential gains from trade, which decreases the queue length λ and puts downward pressure on the asking price.

A similar tension arises if we consider the case where $y_1 = y_2$ but $F_2(x)$ first order stochastic dominates $F_1(x)$. On the one hand, higher valuations for the type 2 good tend to put upward pressure on bids, and hence on the asking price. However, there can be a subtle counter-force: *conditional* on nobody paying a (fixed) asking price, buyers at a type 2 seller will believe that they are facing fewer other buyers, on average, and hence bid less. The final effect on a_i is ambiguous.

For these reasons, the relationship between asking prices across different types of goods is actually quite complicated, and is ultimately a quantitative question that depends on the relative measures of buyers and sellers, the sellers’ valuations for each type of good, and the buyers’ potential valuations. Perhaps these differences can help us understand why some goods tend to typically sell below the asking price, while others more often sell at (or above) the asking price. We leave a more serious exploration for future work.

8 Conclusion

In the majority of existing economic models, it is assumed that either (i) non-negotiable prices are set by sellers; (ii) prices are the outcome of a bargaining game between a single buyer and seller;

³⁵The results are essentially unchanged for $N > 2$ types.

³⁶If the potential gains from trade at type 1 sellers are too small relative to those at type 2 sellers, then no buyer will visit type 1 sellers and that submarket will collapse, i.e. $\lambda_1^* = 0$ (and vice versa).

or (iii) prices are determined through an auction. However, many goods (and services) are sold in a manner that is not consistent with any of these three pricing mechanisms, but rather seems to combine elements of each. First, sellers announce a price, as in models with price-posting, at which they're willing to sell their good or service immediately. However, as in bargaining theory, buyers can submit a counteroffer that will also be considered by the seller. Finally, in the event that no buyer offers the asking price within a certain period of time, the set of counteroffers that the seller has received are aggregated, as in an auction, and the object is awarded to the buyer with the best counteroffer.

Despite the prevalence of this pricing scheme in many markets, it has received little attention in the academic literature. In this paper, our objective was to construct a sensible economic model to help us understand how and why this type of pricing mechanism can be an efficient way of selling goods and services. Combining two simple, realistic ingredients—namely, competition and costly inspection—we showed that asking prices emerge as the mechanism that is both revenue-maximizing and efficient. As a result, the framework developed here provides a theory of asking prices that is both micro-founded and tractable, offers a variety of testable predictions, and lends itself easily to various extensions. Given these features, we believe that our model could be useful for both theoretical and empirical work that focuses on markets in which asking prices are commonly used.

Appendix A: Proofs

Proof of Lemma 1

Proving Lemma 1 requires establishing optimality of both the sequential search strategy and the stopping rule with constant cutoff x^* . Both are well-known results in the literature, so we sketch the intuition below and refer the reader to e.g. Lippman and McCall (1976), Weitzman (1979) and Morgan and Manning (1985) for a more rigorous treatment.

Optimality of Sequential Search. To see that it can never be optimal to learn the valuation of more than one buyer at a time, suppose $n \geq 2$ buyers arrive at a seller, and consider the planner's decision of whether to learn the valuations of the first two buyers sequentially or simultaneously. Let $Z_i(\hat{x}_i) - y$ denote the net expected surplus from continuing to learn buyers' valuations (under the optimal policy) given that the maximum valuation of the seller and the i buyers sampled so far is $\hat{x}_i \equiv \max\{y, x_1, \dots, x_i\}$.

The net social surplus from learning the first two buyers' valuations simultaneously is then

$$-2k - y + \max\{\hat{x}_2, Z_2(\hat{x}_2)\}, \quad (23)$$

whereas the surplus from learning these valuations sequentially is

$$\begin{aligned} & -k - y + \max\{\hat{x}_1, -k + \max\{\hat{x}_2, Z_2(\hat{x}_2)\}\} \\ = & -2k - y + \max\{\hat{x}_1 + k, \hat{x}_2, Z_2(\hat{x}_2)\} \end{aligned} \quad (24)$$

Clearly, the expression in (24) is weakly larger than (23) for any x_1 and x_2 , and strictly larger for some x_1 and x_2 . Taking the expectation over all possible realizations therefore implies that a planner would want to learn these valuations sequentially ex ante. It is straightforward to extend this argument to learning the valuations of $j > 2$ buyers simultaneously after any number $i \leq n - j$ buyers have already inspected the good.

Optimality of the Stopping Rule. Suppose the seller is visited by $n \in \mathbb{N}$ buyers. Let $Z_i(\hat{x}_i)$ denote the expected surplus from sampling the $(i+1)^{th}$ buyer, for $i < n$, and let $V_i(\hat{x}_i) = \max\{\hat{x}_i - y, Z_i(\hat{x}_i)\}$. To derive the optimal stopping rule, we utilize an induction argument. We begin with the first step. If the seller has met with all n buyers, the decision is trivial: the good is allocated to the agent (either one of the buyers or the seller) with valuation \hat{x}_n . The expected surplus is $V_n(\hat{x}_n) = \hat{x}_n - y$.

Working backward, consider the planner's problem when the seller has met with only $n - 1$

of the n buyers. If the planner instructs the seller to stop meeting with buyers, again the good is allocated to the agent with valuation \hat{x}_{n-1} , yielding surplus $\hat{x}_{n-1} - y$. Alternatively, if the seller meets with the next buyer, the expected surplus is $Z_{n-1}(\hat{x}_{n-1}) - y$, where

$$Z_{n-1}(\hat{x}) - y = -k + \int_{\underline{x}}^{\bar{x}} \max \{V_n(\hat{x}), V_n(x)\} f(x) dx,$$

so that

$$Z_{n-1}(\hat{x}) = -k + \hat{x}F(\hat{x}) + \int_{\hat{x}}^{\bar{x}} xf(x) dx. \quad (25)$$

Notice immediately that $Z_{n-1}(x^*) = x^*$ and $\frac{dZ_{n-1}(\hat{x})}{d\hat{x}} = F(\hat{x}) \in (0, 1)$, so that clearly x^* is the optimal cutoff after meeting with $n - 1$ buyers, and

$$V_{n-1}(\hat{x}) = \begin{cases} \hat{x} - y & \text{for } \hat{x} \geq x^* \\ Z_{n-1}(\hat{x}) - y & \text{for } \hat{x} < x^*. \end{cases}$$

Now consider the planner's problem after the seller has met with $n - 2$ buyers. We establish three important properties of $Z_{n-2}(\hat{x})$: (1) $Z_{n-2}(\hat{x}) = Z_{n-1}(\hat{x})$ for all $\hat{x} \geq x^*$; (2) $Z_{n-2}(\hat{x}) > \hat{x}$ for all $\hat{x} < x^*$; and (3) $\lim_{\hat{x} \rightarrow x^*} Z_{n-2}(\hat{x}) = Z_{n-1}(x^*) = x^*$. Given these three properties, along with the fact that $\frac{dZ_{n-2}(\hat{x})}{d\hat{x}} = \frac{dZ_{n-1}(\hat{x})}{d\hat{x}} = F(\hat{x}) \in (0, 1)$ for $x \geq x^*$, it follows immediately that $\hat{x} \geq Z_{n-2}(\hat{x})$ if, and only if, $\hat{x} \geq x^*$, and hence x^* is the optimal cutoff again.

After meeting with $n - 2$ buyers, the expected surplus from another meeting when $\hat{x}_{n-2} = \hat{x}$ is

$$Z_{n-2}(\hat{x}) - y = -k + V_{n-1}(\hat{x})F(\hat{x}) + \int_{\hat{x}}^{\bar{x}} V_{n-1}(x)f(x) dx. \quad (26)$$

If $\hat{x} \geq x^*$, then $V_{n-1}(\hat{x}) = \hat{x} - y$ and thus $Z_{n-2}(\hat{x}) = Z_{n-1}(\hat{x})$. Alternatively, if $\hat{x} < x^*$, then $V_{n-1}(\hat{x}) = Z_{n-1}(\hat{x}) - y > \hat{x} - y$ and

$$\begin{aligned} Z_{n-2}(\hat{x}) &= -k + Z_{n-1}(\hat{x})F(\hat{x}) + \int_{\hat{x}}^{x^*} Z_{n-1}(x)f(x) dx + \int_{x^*}^{\bar{x}} xf(x) dx \\ &> -k + \hat{x}F(\hat{x}) + \int_{\hat{x}}^{x^*} xf(x) dx + \int_{x^*}^{\bar{x}} xf(x) dx \\ &= Z_{n-1}(\hat{x}) > \hat{x}. \end{aligned}$$

Finally, note that

$$\begin{aligned}
\lim_{\hat{x} \rightarrow x^*} Z_{n-2}(\hat{x}) &= -k + Z_{n-1}(x^*) F(x^*) + \int_{x^*}^{\bar{x}} x f(x) dx \\
&= -k + x^* F(x^*) + \int_{x^*}^{\bar{x}} x f(x) dx \\
&= Z_{n-1}(x^*) = x^*.
\end{aligned}$$

Therefore, the optimal cutoff after meeting with $n - 2$ buyers is x^* .

We have established that the following is true for $j' = 2$:

1. $Z_{n-j'}(\hat{x}) = Z_{n-j'+1}(\hat{x})$ for all $\hat{x} \geq x^*$.
2. $Z_{n-j'}(\hat{x}) > \hat{x}$ for all $\hat{x} < x^*$.
3. $\lim_{\hat{x} \rightarrow x^*} Z_{n-j'}(\hat{x}) = Z_{n-j'+1}(x^*) = x^*$,

so that

$$V_{n-j'}(\hat{x}) = \begin{cases} \hat{x} - y & \text{for } \hat{x} \geq x^* \\ Z_{n-j'}(\hat{x}) - y & \text{for } \hat{x} < x^*. \end{cases}$$

Now, suppose this is true for all $j' \in \{2, 3, \dots, j\}$. We will establish that it is also true for $j + 1$. After meeting with $n - j - 1$ buyers, the expected surplus from another meeting when $\hat{x}_{n-j-1} = \hat{x}$ is

$$Z_{n-j-1}(\hat{x}) - y = -k + V_{n-j}(\hat{x}) F(\hat{x}) + \int_{\hat{x}}^{\bar{x}} V_{n-j}(x) f(x) dx. \quad (27)$$

If $\hat{x} \geq x^*$, then $V_{n-j}(\hat{x}) = \hat{x} - y$ and thus $Z_{n-j-1}(\hat{x}) = Z_{n-1}(\hat{x})$. Moreover, given the first assumption in the induction step, $Z_{n-j}(\hat{x}) = Z_{n-1}(\hat{x})$, so that $Z_{n-j-1}(\hat{x}) = Z_{n-j}(\hat{x})$.

Alternatively, if $\hat{x} < x^*$, then

$$\begin{aligned}
Z_{n-j-1}(\hat{x}) &= -k + Z_{n-j}(\hat{x}) F(\hat{x}) + \int_{\hat{x}}^{x^*} Z_{n-j}(x) f(x) dx + \int_{x^*}^{\bar{x}} x f(x) dx \\
&> -k + \hat{x} F(\hat{x}) + \int_{\hat{x}}^{\bar{x}} x f(x) dx = Z_{n-1}(\hat{x}) > \hat{x}
\end{aligned}$$

Finally, note that

$$\begin{aligned}
\lim_{\hat{x} \rightarrow x^*} Z_{n-j-1}(\hat{x}) &= -k + Z_{n-j}(x^*) F(x^*) + \int_{x^*}^{\bar{x}} x f(x) dx \\
&= Z_{n-1}(x^*) = x^*.
\end{aligned}$$

Therefore, we have that the optimal cutoff after meeting with $n - j - 1$ buyers is x^* . ■

Proof of Lemma 2

Substituting (2) into (6) and integrating by parts yields

$$S(x^*, \lambda) = x^* - y - \int_y^{x^*} q_0(x) dx.$$

Since x^* is independent of λ , the second derivative of $S(x^*, \lambda)$ with respect to λ then equals

$$\frac{d^2 S}{d\lambda^2} = - \int_y^{x^*} (1 - F(x))^2 q_0(x) dx < 0.$$

■

Proof of Proposition 1

Given Lemma 1, clearly a stopping rule of x^* is optimal at all sellers. Then, given Lemma 2, it follows that total surplus is maximized by assigning the same queue length $\lambda = \Lambda$ to all sellers. ■

Proof of Lemma 3

When the buyer declines to pay the asking price, he realizes that the auction will take place if and only if all other buyers visiting the same seller have a valuation below x^a . In the auction, the buyer will face a number of competitors which follows a Poisson distribution with mean $\lambda F(x^a)$. Their valuations will be distributed according to $\frac{F(x)}{F(x^a)}$. Standard arguments imply that the expected payoff for the buyer from participating in the auction equals the integral of his trading probability.³⁷ That is,

$$\int_y^x e^{-\lambda F(x^a)(1 - \frac{F(\tilde{x})}{F(x^a)})} d\tilde{x} = \int_y^x \frac{q_0(\tilde{x})}{q_0(x^a)} d\tilde{x}, \quad (28)$$

where the integrand represents the probability that no other buyer has a valuation above \tilde{x} , conditional on all valuations being below x^a . Multiplying this payoff by (7) yields the desired expression for $u(x)$.

To derive the buyer's optimal bidding function $\hat{b}(x)$ in the first-price auction, note that (28) should be equal to the product of the probability that the buyer wins the auction and his payoff conditional on winning. That is,

$$\frac{q_0(x)}{q_0(x^a)} (x - b(x)) = \int_y^x \frac{q_0(\tilde{x})}{q_0(x^a)} d\tilde{x},$$

³⁷See Peters (2013) for a detailed discussion. Peters and Severinov (1997) explicitly analyze the case with a Poisson number of buyers.

where the first factor on the left-hand side represents the probability that no other buyer has a valuation above x , conditional on all valuations being below x^a . Solving for $\widehat{b}(x)$ gives the desired result. ■

Proof of $\frac{da}{dx^a} > 0$

Differentiating (11) yields

$$\frac{da}{dx^a} = \frac{1 - q_0(x^a) - q_1(x^a)}{1 - q_0(x^a)} \left(1 + \frac{\lambda f(x^a)}{1 - q_0(x^a)} \int_y^{x^a} q_0(x) dx \right) > 0.$$

■

Proof of Proposition 2

Since the relation between a and x^a is one-to-one, given λ , the seller's maximization problem can be rewritten as a choice over x^a and λ , which turns out to be more convenient analytically. Define $\widehat{R}(x^a, \lambda)$ as the revenue of a seller with asking price a , queue λ and cutoff $x^a \equiv x^a(a, \lambda)$. Substituting a and $\widehat{b}(x)$ into $R(a, \lambda)$, as given in (15), yields

$$\widehat{R}(x^a, \lambda) = x^a - (1 + \lambda) \int_y^{x^a} q_0(\widehat{x}) d\widehat{x} + \lambda \int_y^{x^a} F(x) q_0(x) dx.$$

One can derive $\widehat{U}(x^a, \lambda)$, i.e., the expected payoff of a buyer visiting this seller, in a similar fashion:

$$\widehat{U}(x^a, \lambda) = \frac{1}{\lambda} \left(\frac{1 - q_0(x^a)}{(1 - F(x^a))} \left[\int_{x^a}^{\bar{x}} (x - x^a) dF(x) - k \right] + \lambda \int_y^{x^a} (1 - F(x)) q_0(x) dx \right). \quad (29)$$

The partial derivatives of $\widehat{R}(x^a, \lambda)$ are equal to

$$\begin{aligned} \frac{\partial \widehat{R}}{\partial x^a} &= 1 - Q_1(x^a) > 0 \\ \frac{\partial \widehat{R}}{\partial \lambda} &= \lambda \int_y^{x^a} (1 - F(x))^2 q_0(x) dx > 0 \end{aligned}$$

while the partial derivatives of $\widehat{U}(x^a, \lambda)$ are

$$\begin{aligned}\frac{\partial \widehat{U}}{\partial x^a} &= -\frac{1 - Q_1(x^a)}{\lambda} \left(1 - \frac{f(x^a)}{(1 - F(x^a))^2} \left[\int_{x^a}^{\bar{x}} (x - x^a) dF(x) - k \right] \right) < 0 \\ \frac{\partial \widehat{U}}{\partial \lambda} &= -\frac{1 - Q_1(x^a)}{\lambda^2 (1 - F(x^a))} \left[\int_{x^a}^{\bar{x}} (x - x^a) dF(x) - k \right] - \int_y^{x^a} q_0(x) (1 - F(x))^2 dx,\end{aligned}$$

since $Q_1(x^a) < 1$. Therefore, the first-order conditions of the Lagrangian with respect to x_a , λ , and μ , respectively, equal

$$0 = (1 - Q_1(x^a)) \left(1 - \frac{\mu}{\lambda} \left(1 - \frac{f(x^a)}{(1 - F(x^a))^2} \left[\int_{x^a}^{\bar{x}} (x - x^a) dF(x) - k \right] \right) \right) \quad (30)$$

$$\begin{aligned}0 &= \lambda \int_y^{x^a} q_0(x) (1 - F(x))^2 dx \left(1 - \frac{\mu}{\lambda} \right) \\ &\quad - \frac{\mu}{\lambda^2} \frac{1 - Q_1(x^a)}{(1 - F(x^a))} \left[\int_{x^a}^{\bar{x}} (x - x^a) dF(x) - k \right] \quad (31)\end{aligned}$$

$$0 = \frac{1 - q_0(x^a)}{\lambda (1 - F(x^a))} \left[\int_{x^a}^{\bar{x}} (x - x^a) dF(x) - k \right] + \int_y^{x^a} (1 - F(\hat{x})) q_0(\hat{x}) d\hat{x} - \bar{U}.$$

Solving (30) implies

$$\frac{\mu}{\lambda} = \left(1 - \frac{f(x^a)}{(1 - F(x^a))^2} \left[\int_{x^a}^{\bar{x}} (x - x^a) dF(x) - k \right] \right)^{-1},$$

so that (31) can be written as

$$\begin{aligned}0 &= \left[\int_{x^a}^{\bar{x}} (x - x^a) dF(x) - k \right] \times \\ &\quad \frac{\mu}{\lambda} \left\{ -\frac{\lambda f(x^a) \int_y^{x^a} q_0(x) (1 - F(x))^2 dx}{(1 - F(x^a))^2} - \frac{1 - Q_1(x^a)}{\lambda (1 - F(x^a))} \right\}.\end{aligned}$$

Since the term in brackets on the second line of this equation is strictly negative, it must be that the unique solution for x^a satisfies $\int_{x^a}^{\bar{x}} (x - x^a) dF(x) = k$. From this, it immediately follows that $x^a = x^*$ and $\mu = \lambda = \Lambda$. Hence, the equilibrium is unique and it coincides with the solution to the planner's problem. Given $x^a = x^*$ and $\lambda = \Lambda$, the optimal asking price follows from (11). ■

Proof of Proposition 3

Consider a candidate equilibrium with market utility $0 < \bar{U} < \int_y^{\bar{x}} (x - y) f(x) dx - k$. Now, take an arbitrary mechanism m_1 that one or more sellers post in this equilibrium, which attracts a queue

$\lambda_1 > 0$ that satisfies $\mathbf{U}(m_1, \lambda_1) = \bar{U}$. This mechanism yields the seller a payoff $\mathbf{R}(m_1, \lambda_1)$ and generates a surplus $\mathbf{S}(m_1, \lambda_1) = \mathbf{R}(m_1, \lambda_1) + \lambda_1 \mathbf{U}(m_1, \lambda_1) - y$.

Now consider an asking price mechanism m_a^* that implements the cutoff x^* and attracts a queue length $\lambda_a > 0$ that satisfies $\bar{U} = \mathbf{U}(m_a^*, \lambda_a)$.³⁸ From our results in Proposition 2, and the discussion that follows, we know that $\mathbf{S}(m_a^*, \lambda_a) = \mathbf{S}^*(\lambda_a)$ and

$$\left. \frac{\partial \mathbf{S}^*(\lambda)}{\partial \lambda} \right|_{\lambda=\lambda_a} = \bar{U}. \quad (32)$$

Since m_1 was chosen when m_a^* was feasible, it must be that

$$\mathbf{S}^*(\lambda_a) - \lambda_a \bar{U} + y = \mathbf{R}(m_a^*, \lambda_a) \leq \mathbf{R}(m_1, \lambda_1) = \mathbf{S}(m_1, \lambda_1) - \lambda_1 \bar{U} + y.$$

Next, let $\lambda^* = \arg \max_{\lambda} \mathbf{S}^*(\lambda) - \lambda \bar{U}$. Since $\mathbf{S}^*(\lambda)$ is strictly concave, we are assured of a unique solution that will satisfy

$$\left. \frac{\partial \mathbf{S}^*(\lambda)}{\partial \lambda} \right|_{\lambda=\lambda^*} = \bar{U}.$$

From (32), it must be that $\lambda^* = \lambda_a$. Moreover, since $\mathbf{S}(m_1, \lambda_1) \leq \mathbf{S}^*(\lambda_1)$, we can write

$$\begin{aligned} \mathbf{R}(m_1, \lambda_1) = \mathbf{S}(m_1, \lambda_1) - \lambda_1 \bar{U} + y &\leq \mathbf{S}^*(\lambda_1) - \lambda_1 \bar{U} + y \\ &\leq \mathbf{S}^*(\lambda^*) - \lambda^* \bar{U} + y \\ &= \mathbf{S}^*(\lambda_a) - \lambda_a \bar{U} + y = \mathbf{R}(m_a^*, \lambda_a). \end{aligned}$$

Hence, for any equilibrium mechanism m_1 , it must be that $\mathbf{R}(m_1, \lambda_1) = \mathbf{R}(m_a^*, \lambda_a)$. Moreover, it must also be that $\lambda_1 = \lambda_a = \lambda^*$. Otherwise, for any $\lambda_1 \neq \lambda^*$, $\mathbf{R}(m_1, \lambda_1) \leq \mathbf{S}^*(\lambda_1) - \lambda_1 \bar{U} + y < \mathbf{S}^*(\lambda^*) - \lambda^* \bar{U} + y = \mathbf{R}(m_a^*, \lambda_a)$. This concludes the proof of Proposition 3.

Finally, since these results hold for all sellers, it must be that $\lambda^* = \Lambda$ in equilibrium. Therefore, for any m_1 offered in equilibrium, we must $\lambda_1 = \Lambda$, $\mathbf{U}(m_1, \lambda) = \mathbf{U}(m_a^*, \Lambda) = \bar{U}^*$ and $\mathbf{R}(m_1, \lambda_1) = \mathbf{R}(m_a^*, \Lambda) = \mathbf{S}^*(\Lambda) - \Lambda \bar{U} + y$; this is the result reported in Corollary 2.

Proof of Lemma 4

Consider a seller with n buyers. The sale price will be above asking price if $i \in \{2, \dots, n\}$ buyers draw a valuation between a and x^a while the remaining $n - i$ buyers draw a valuation below a .

³⁸Note that λ_a depends on \bar{U} . However, in what follows, we suppress this implicit relationship for notational convenience.

The probability of this event equals

$$\sum_{i=2}^n \frac{n!}{i! (n-i)!} (F(x^a) - F(a))^i F(a)^{n-i},$$

which simplifies to

$$F(x^a)^n - n(F(x^a) - F(a))F(a)^{n-1} - F(a)^n.$$

Taking the expectation over n yields the desired expression. ■

Proof of Lemma 5

For the planner's problem, the proof proceeds by induction, much like the proof of lemma 1. Suppose that n buyers visit a seller, the first $n - 1$ buyers learn their valuation, and no trade has taken place because $\hat{x}_{n-1} \equiv \max\{y, x_1, \dots, x_{n-1}\} < x^*$. In this case, the planner has two options: either let buyer n incur the inspection cost k and base the ensuing trading decision on \hat{x}_n , or avoid the inspection cost by instructing the seller to trade with buyer n without knowing his valuation.³⁹

In the former case, expected surplus generated by the match is $Z_{n-1}(\hat{x}_{n-1}) - y$, where

$$Z_{n-1}(\hat{x}) = -k + \hat{x}F(\hat{x}) + \int_{\hat{x}}^{\bar{x}} xf(x) dx,$$

while the latter case yields an expected surplus equal to $\int_{\underline{x}}^{\bar{x}} xf(x) dx - y$. Clearly, inspection is preferred if and only if $Z_{n-1}(\hat{x}_{n-1}) - y > \int_{\underline{x}}^{\bar{x}} xf(x) dx - y$, or equivalently

$$k < \int_{\underline{x}}^{\hat{x}_{n-1}} (\hat{x}_{n-1} - x) f(x) dx.$$

This condition needs to hold for any feasible value of \hat{x}_{n-1} in order to guarantee inspection by the last buyer. Since the right-hand side is strictly increasing in \hat{x}_{n-1} , (22) is a necessary and sufficient condition. The final step is then to show that this condition implies that inspection is also optimal after meeting with $n - j - 1$ buyers for $j \in \{1, \dots, n - 1\}$. This follows immediately from $Z_{n-j-1}(\hat{x}) \geq Z_{n-1}(\hat{x})$ for all \hat{x} and j , as shown in the proof of lemma 1.

Next, we analyze the market equilibrium described in section 4. Consider a deviating buyer who does not inspect the good and therefore does not know his valuation. This deviant has three options: 1) submit a bid below y , which will be rejected; 2) submit a bid between y and a ; or

³⁹The planner can of course also instruct the seller to immediately trade with the agent with valuation \hat{x}_{n-1} , but, as shown in lemma 1, this is dominated by learning the valuation of the last buyer since $\hat{x}_{n-1} < x^*$.

3) bid the asking price and trade immediately. The choice between these options is equivalent to choosing a type of buyer $x' \in [\underline{x}, \bar{x}]$ to mimic.

We first establish that it is optimal for the deviant to behave like a buyer who has a valuation x' equal to the unconditional expected value of x , which we denote by $x^e = E_F[x] \equiv \int_{\underline{x}}^{\bar{x}} x f(x) dx$. To see this, consider the expected payoffs under each of the three options. First, a deviant who acts like a buyer with valuation $x' \in [\underline{x}, y]$ receives a payoff of 0. Second, if the deviant instead imitates a buyer of type $x' \in (y, x^a)$ and bids $\hat{b}(x')$, his payoff conditional on meeting with the seller is

$$u(x'|x^e) = \frac{\lambda(1 - F(x^a))q_0(x')}{1 - q_0(x^a)} [x^e - \hat{b}(x')].$$

Since $\hat{b}(x')$ is optimal in equilibrium, it follows that the deviant should choose $x' = x^e$ and bid $\hat{b}(x^e)$. Evaluating the expected payoff from this strategy yields

$$u(x^e) = \frac{\lambda(1 - F(x^*))}{1 - q_0(x^*)} \int_y^{x^e} q_0(\tilde{x}) d\tilde{x}, \quad (33)$$

where $u(x^e)$ is increasing and convex in its argument. Finally, if the deviant mimics a buyer of type $x' \in [x^*, \bar{x}]$ and bids the asking price, he obtains a payoff

$$x^e - a^* = x^e - x^* + u(x^*). \quad (34)$$

Comparing the three payoffs reveals that the deviant maximizes his payoff by behaving as a buyer with valuation x^e . That is, he should submit a bid below y if $x^e < y$ and should bid $\hat{b}(x^e)$ if $x^e \in [y, x^*]$. Note that the remaining case, $x^e \in [x^*, \bar{x}]$, cannot occur under (22), since it implies

$$\begin{aligned} x^e &= - \int_{\underline{x}}^{x^*} (x^* - x) f(x) dx + k + x^* \\ &< - \int_{\underline{x}}^y (y - x) f(x) dx + k + x^* < x^*. \end{aligned}$$

To see whether the deviant benefits from not inspecting the good, define an auxiliary distribution $\tilde{F}(x)$ that resembles $F(x)$, except that the mass below y and above x^* is concentrated as mass points at y and x^* , respectively. That is,

$$\tilde{F}(x) = \begin{cases} 0 & \text{if } x < y \\ F(x) & \text{if } y \leq x \leq x^* \\ 1 & \text{if } x^* < x. \end{cases}$$

Let $\tilde{x}^e = E_{\tilde{F}}[x]$ denote the expectation of x under this modified distribution. Under (22), it then follows that $\tilde{x}^e > x^e$, since

$$\begin{aligned}\tilde{x}^e - x^e &= \int_{\underline{x}}^y (y - x) dF(x) - \int_{x^*}^{\bar{x}} (x - x^*) dF(x) \\ &= \int_{\underline{x}}^y (y - x) dF(x) - k > 0.\end{aligned}$$

The fact that $u(x)$ is an increasing function then implies that $u(x^e) < u(\tilde{x}^e)$, while the convexity of $u(x)$ implies that $u(\tilde{x}^e) < E_{\tilde{F}}[u(x)]$ by Jensen's inequality. Note, however, that $E_{\tilde{F}}[u(x)]$ exactly equals the payoff from inspection, since

$$\begin{aligned}E_{\tilde{F}}[u(x)] &= u(y) \tilde{F}(y) + \int_y^{x^*} u(x) d\tilde{F}(x) + (1 - \tilde{F}(x^*)) u(x^*) \\ &= \int_y^{x^*} u(x) dF(x) + (1 - F(x^*)) u(x^*) \\ &= \frac{\lambda(1 - F(x^a))}{1 - q_0(x^a)} \left[\int_y^{x^*} \int_y^x q_0(\tilde{x}) d\tilde{x} dF(x) + (1 - F(x^*)) \int_y^{x^*} q_0(\tilde{x}) d\tilde{x} \right]\end{aligned}$$

Hence, the payoff from inspection is strictly higher than the payoff from not inspecting.

To show that equation (22) is also necessary, consider the limit $\Lambda \rightarrow 0$, such that a buyer who meets with a seller knows that, with probability 1, he does not face competition from other buyers. The optimal bid in that case is y and it follows immediately that inspection is better only if equation (22) holds. ■

Proof of Lemma 6

Compared to the homogeneous model, the environment gives rise to one extra decision, which concerns the allocation of buyers across the two goods. Suppose that a fraction ψ_i of the buyers is allocated to sellers of good i , with $\psi_1 + \psi_2 = 1$. Conditional on ψ_i , the game within each submarket is essentially the same as in the homogeneous model. Hence, it follows directly from proposition 1 that a planner assigns each seller of good i a queue $\lambda_i(\psi_i) = \frac{\psi_i}{\phi_i} \Lambda$ and instructs him to implement a cutoff x_i^* , which is the solution to $k = \int_{x_i^*}^{\bar{x}} (x - x_i^*) f_i(x) dx$. The surplus created by the seller then equals

$$\mathbf{S}_i^*(\lambda(\psi_i)) = x_i^* - y_i - \int_{y_i}^{x_i^*} e^{-\lambda_i(\psi_i)(1-F_i(x))} dx.$$

Conditional on sellers using asking price mechanisms, it follows from proposition 2 that—for a given ψ_i —all sellers of good i post an asking price equal to

$$a_i(\psi_i) \equiv x_i^* - \frac{\lambda_i(\psi_i)(1 - F_i(x_i^*))}{1 - e^{-\lambda_i(\psi_i)(1 - F_i(x_i^*))}} \int_{y_i}^{x_i^*} e^{-\lambda_i(\psi_i)(1 - F_i(x))} dx.$$

A buyer who visits a seller of good i obtains an expected payoff

$$\bar{U}_i(\psi_i) = \int_{y_i}^{x_i^*} (1 - F_i(x)) e^{-\lambda_i(\psi_i)(1 - F_i(x))} dx,$$

which is exactly his marginal contribution to surplus, $\frac{\partial}{\partial \lambda} \mathbf{S}_i^*(\lambda(\psi_i))$. Hence, by proposition 3, asking price mechanisms are optimal even when sellers have access to a larger mechanism space.

Consider now the allocation of buyers to the two different goods. In the decentralized market, each buyer chooses the submarket that maximizes his expected payoff, while a planner wants to allocate buyers to the submarket in which their marginal contribution of surplus is highest. Since $\bar{U}_i(\psi_i) = \frac{\partial}{\partial \lambda} \mathbf{S}_i^*(\lambda(\psi_i))$, these choices will coincide. There are three possible cases:

1. If $\bar{U}_1(0) \leq \bar{U}_2(1)$, then $\psi_1^* = 0$ and $\psi_2^* = 1$. That is, all buyers visit sellers of good 2.
2. If $\bar{U}_1(1) \geq \bar{U}_2(0)$, then $\psi_1^* = 1$ and $\psi_2^* = 0$. That is, all buyers visit sellers of good 1.
3. If $\bar{U}_1(0) > \bar{U}_2(1)$ and $\bar{U}_1(1) < \bar{U}_2(0)$, then—by the Intermediate Value Theorem—there exists a $\psi_1^* \in (0, 1)$ such that $\bar{U}_1(\psi_1^*) = \bar{U}_2(1 - \psi_1^*)$. That is, buyers randomize between the sellers.

■

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Figure 1: Optimal Mechanisms

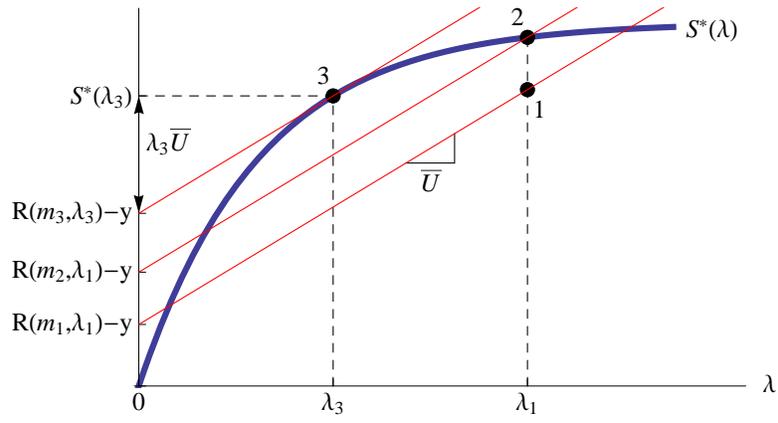


Figure 2: Transaction Price CDF

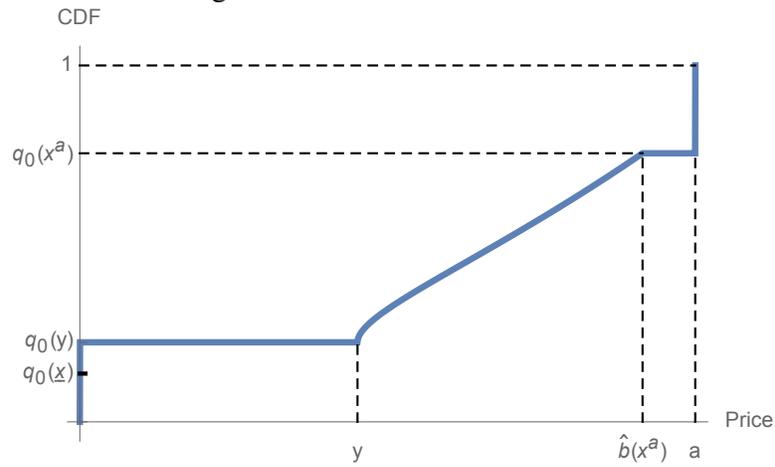
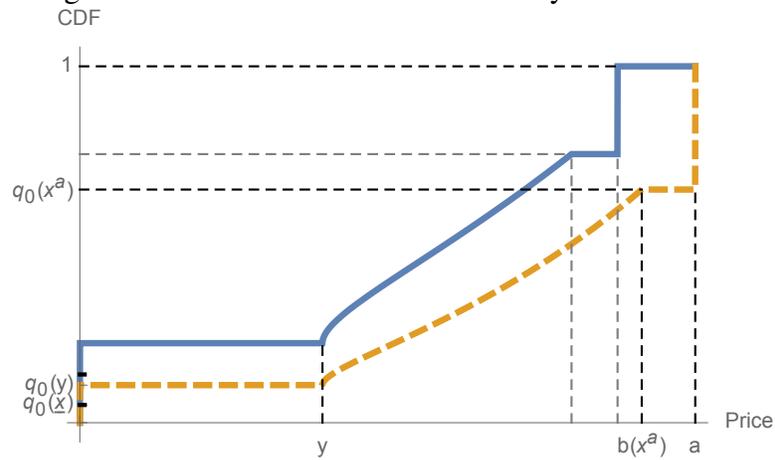
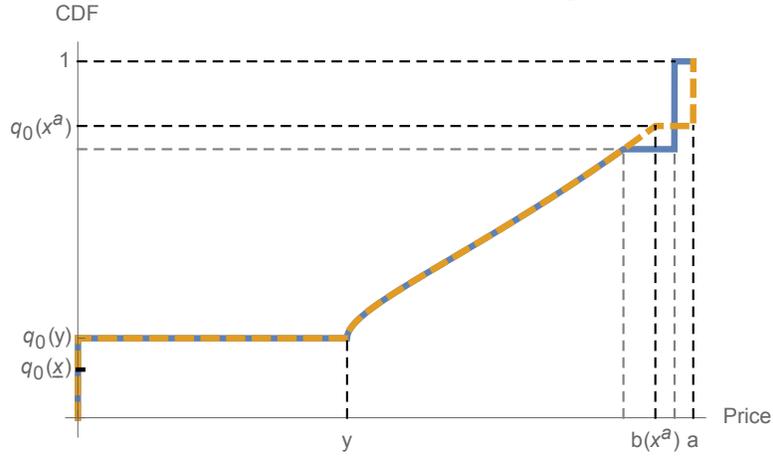


Figure 3: Effect of an Increase in the Buyer/Seller Ratio



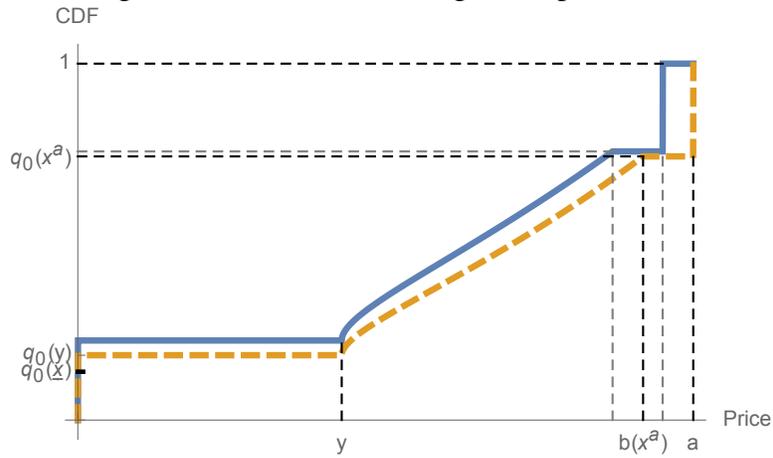
solid blue line = original equilibrium; dashed orange line = equilibrium with higher Λ .

Figure 4: Effect of a Decrease in the Inspection Cost



solid blue line = original equilibrium; dashed orange line = equilibrium with lower k .

Figure 5: Effect of Technological Improvement



solid blue line = original equilibrium; dashed orange line = equilibrium with more information.

Figure 6: Transaction Prices Above the Asking Price

