Using aggregate market data to estimate patent value

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ABSTRACT

Intellectual property and its protection is one of the most valuable assets for entrepreneurs and firms in the information economy. This article describes a relatively straightforward method for measuring patent value with aggregate market data and the BLP model. We apply the method to United States smartphones. The demand estimates and recovered marginal costs produce sensible simulations of equilibria prices and shares from several hypothetical patent infringements. In one simulation, the presence of near field communication on the dominant firm's flagship smartphone results in a 26 percent increase in profits per phone. This estimate provides a starting point for establishing a reasonable royalty between the patent holder and the dominant firm in a hypothetical negotiation. This simulation also shows that law-abiding firms inside the market may be damaged by the dominant firm's infringing behavior.

Key words: intellectual property, random-coefficient logit demand, patent, smartphones

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1. Introduction

Intellectual property and its protection with patents is arguably one of the most valuable assets for entrepreneurs and firms in the information economy. This article describes a relatively straightforward method for measuring patent value with aggregate market data on sales, prices and product characteristics and the static oligopoly model of Berry, Levinsohn and Pakes (1995) (BLP hereafter). The method can be applied to the calculation of damages and a reasonable royalty in intellectual property cases, and to the calculation of damages in trademark, copyright, trade-secret, and breach of contract cases.

The total number of utility patent applications in the United States increased from 90,643 per annum in 1990 to 288,335 in 2015 with much of the growth in computing, software, telecommunications and mobile technologies (U.S. Patent and Trademark Office, 2016). Cellular telephones, for example, accounted for about 16 percent of the total patents active at 2012, compared to six percent from the pharmaceutical industry. Not surprisingly, the number of patent suits filed each year has more than tripled over the same period from about 1,500 to 5,250 making innovation and market entry more costly for entrepreneurs negotiating licenses or settling disputes through the courts. The important economic costs in these settlements are the defendant's lost profits from illegal use of the patent-infringing product characteristic or "patent damages." Careful measurement of patent damages is paramount given that several recent awards have approached and exceeded one billion dollars including, for example, Polaroid Corp v. Eastman Kodak Co. (1990), and Apple v. Samsung (2012).

Two common approaches for estimating patent damages are stated-choice methods and natural experiments (Cameron, et al., 2014). Stated-choice methods use choice experiments to solicit stated preferences in a hypothetical setting administered by survey. These are appropriate when the researcher cannot observe (or, cleanly measure) product sales with and without the infringing characteristic. Natural experiments occur when product sales can be observed in the market. Because market data reflect the revealed preferences of consumers and the profit-maximizing decisions of firms, they typically provide good quality information for quantifying the consumer's marginal willingness-to-pay (WTP) for a patented characteristic and the associated change in profits. We use these data to estimate demand as a function of product characteristics, preferences, and unobservable utility. The demand parameters and recovered marginal costs are used to simulate firm profits in the baseline equilibrium without the patented characteristic and a new equilibrium when this characteristic is added to the infringing products, allowing the calculation of changes in prices, market shares, and profits.

We apply the patent evaluation method to quarterly data on United States smartphone sales from 2010 to 2015. The data fit the demand specification well as judged by the estimated positive preferences for most smartphone characteristics. For example, the representative consumer is willing to pay $98 for an additional inch of screen size, $10 for an additional megapixel of camera resolution, $64 for fourth-generation (4G) network compatibility and $87 for near field communication (NFC). There is also a large consumer premium for the dominant firm's brand name of $687. The demand estimates and recovered marginal costs produce economically sensible counterfactual simulations of equilibria prices and market shares from several different hypothetical patent infringements under Bertrand competition. In one simulation, the presence of NFC on the dominant firm's flagship smartphone results in a 26 percent increase in profits per phone. This estimate provides a starting point for establishing a reasonable royalty between the patent holder and the dominant firm in a hypothetical negotiation.

Formal economic studies on the estimation of patent damages are sparse. Allenby et al. (2014) apply stated-choice methods to digital cameras and show that demand-side evaluation alone can sometimes overstate patent value because it omits equilibrium profits. Falk and Train (2016) compare the number of present and future citations the patent has received to the numbers received by other patents whose market values are established through negotiated royalties. In a related literature, Goldfarb et al. (2009) use a BLP model and market data to measure breakfast cereal brand value as the difference in equilibrium profits between the brand in question and its counterfactual unbranded equivalent. Sun (2012) uses a similar approach to show how applications contributed to the growth in brand value of the iPhone, BlackBerry, and Android operating systems. Our research is also related to antitrust studies of market power, for example, Nevo (2000) for cereal. Closer to the market we consider, Fan and Yang (2016) show that when the United States smartphone market contains little variety, less competition decreases both the number and variety of products.

Relative to these literatures our study makes several contributions. To the best of our knowledge this is the first publicly-available paper to measure patent damages in an equilibrium framework from transactions observed in the market. By using observational data, our estimates more accurately reflect the revealed preferences of consumers in the marketplace, which should have more credibility in a patented product characteristic case. Application of the BLP estimator also alleviates concerns about price endogeneity that, as argued by Allenby et al. (2014), often "render observational data uninformative with respect to price sensitivity." Because it quantifies the effects on firms inside the market not involved in the patent dispute, the equilibrium framework also shows that law-abiding firms may lose market share and pricing power as result of the dominant firm's ("anti-competitive") infringing behavior. This insight has been largely overlooked in the literature and should be of interest to legal scholars studying third-party damages claims and to game theorists studying the strategic behavior of patent registration, violation and enforcement. We also offer new evidence on consumer preferences and market power in smartphone markets, and use the proposed method to illustrate the lost value from brand degradation through potential breach of contract by a component supplier. As an aside, we discuss how stated-choice utility coefficients, which are occasionally more precisely estimated, can be included in the demand-side of the economic framework to validate or potentially improve the measurement of damages.

The paper is organized as follows. Section 2 describes the empirical model and the data are presented in Section 3. Section 4 presents the demand results and Section 5 uses these estimates and recovered marginal costs to simulate patent damages under several alternative scenarios. Section 6 concludes.

2. Empirical model

2.1 Background

The *Panduit* test provides the starting point for measuring patent value. The test requires that the plaintiff establish demand for the patented product characteristic, an absence of acceptable non-infringing substitutes, manufacturing and marketing capability to exploit the demand, and the amount of profit that would have been made.[2] When these conditions are met, values can be calculated in a similar fashion to the benefits and costs in antitrust cases for price fixing and mergers. This requires specification of an economic model of demand, supply and competition as suggested by BLP, and the construction of counterfactual markets where the

[2] Panduit Corp. v. Stablin Bros. Fibre Works, Inc., 575 F.2d 1152 (Sixth Circuit 1978). See Keeley (1999) and Sidak (2016) for a more detailed description of the law and economics of patent infringement cases.

potential patent infringement is absent and present. When the patent holder is inside the market, patent value is measured by its lost profits from lost sales and price erosion as a result of the infringement (Patent Act of 1946, 2011). When the patent holder is outside of the market, the profits earned by the infringing firm provide a starting point for establishing a reasonable royalty rate between the patent holder and the infringing firm in a hypothetical negotiation over the legal use of this technology.

2.2 Demand

To estimate the impact of an infringing product characteristic, we begin by specifying a random-coefficient logit (RCL) model of consumer demand in a differentiated product market. Demand is described by the random-utility framework where the consumer can choose to purchase the product in question (e.g., digital camera, DVR, game console, smartphone, Tablet, etc.) or choose the outside option of no purchase (McFadden, 1974). The utility consumer $i = 1, 2, \ldots, N$ obtains from purchasing product $j = 1, 2, \ldots, J$ in time period $t = 1, 2, \ldots, T$ is:

$$u_{ijt} = x_{jt}'\beta_i - \alpha p_{jt} + \lambda_{f(j)} + \gamma_t + \xi_{jt} + \varepsilon_{ijt} \tag{1}$$

where x_{jt} is a $K \times 1$ vector of product characteristics k for model j in period t, p_{jt} is the price of product j in period t, $\lambda_{f(j)}$ is a time-invariant brand fixed effect that measures the consumer's average preferences for a brand with $f(j)$ indicating the manufacturing firm f for model j, γ_t is a product-invariant fixed effect that controls for changes in consumer's preferences for smartphones through time, ξ_{jt} is an unobserved demand shock for product j in period t, β_i is a $K \times 1$ vector of marginal utilities for the k non-price product characteristics, α is the marginal utility of income, and ε_{ijt} is an unobserved random error term that is assumed to be independently and identically distributed extreme value.

We follow the standard approach in the literature and assume that the demand parameters for the non-price characteristics are independently and identically distributed random variables that vary across the population of consumers according to the normal distribution $\beta_i \sim \mathrm{N}(\beta, \Sigma)$, where β and Σ are the reparameterization to be estimated. The mean utility for product j at time t is described by $\delta_{jt} = x_{jt}'\beta - \alpha p_{jt} + \lambda_{f(j)} + \gamma_t + \xi_{jt}$ and the mean utility from the outside option $j = 0$ is normalized to zero.

Since the error term ε_{ijt} is distributed type I extreme value, the market shares for all products and the outside good at time t for a given set of demand parameters is:

$$s_{jt} = \int \frac{exp(x_{jt}'\beta_i - \alpha p_{jt} + \lambda_{f(j)} + \gamma_t + \xi_{jt})}{1 + \sum_{k=1}^{J} exp(x_{kt}'\beta_i - \alpha p_{kt} + \lambda_{f(k)} + \gamma_t + \xi_{kt})} dG(\beta_i) \tag{2}$$

which is interpreted as the weighted sum of the individual consumer choice probabilities across the whole population, with the weights given by the probability distribution $G(\beta_i)$. The $J \times 1$ vector of mean utilities for each period can be retrieved and solved for the demand parameters using the contraction mapping suggested by BLP and non-linear generalized method of moments (GMM). The identifying assumption for the non-linear GMM estimator is:

$$E[\xi_{jt} \mid z_{jt}] = 0 \tag{3}$$

where z_{jt} is a $R \times 1$ vector of instruments with $R - K > 0$ excluded instruments correlated with price but uncorrelated with the structural error term. In the supply-side below, the estimated demand parameters α, β, $\lambda_{f(j)}$, γ_t , ξ_{jt} and Σ are used to calculate the vector of product market shares for each period as well as the matrix of share price derivatives.

2.3 Supply-side and the equilibrium calculation of patent damages

The supply-side is described by a static Bertrand game with constant marginal costs. For ease of notation, we assume a given time period for supply and omit the time subscript from subsequent description of the economic model. There are $f = 1, 2, \ldots, F$ firms, with each firm producing some subset, $\Re_f$, of the j different products. Profits for firm f are:

$$\pi_f = \sum_{j \in \Re_f} \left(p_j - mc_j\right) M s_j(p) - FC_f \tag{4}$$

where mc_j is the constant marginal cost of product j, M is market size or the number of customers who may potentially buy a product, $s_j(p)$ is the market share of product j, which is a function of all product prices represented by the vector p, $Ms_j(p)$ is the quantity of product j sold in the market, and FC_f is the fixed cost of production for firm f.

In the static Bertrand oligopoly model, firms set profit-maximizing prices in response to what they expect their rivals do. Specifically, each firm is assumed to choose prices that maximize profits given the demand functions and characteristics of its own products and the prices, demand functions and characteristics for competing products. Firm entry and exit decisions are assumed exogenous to the pricing decision. Given the existence of a pure-strategy Bertrand-Nash equilibrium in prices, and the prices that support it are strictly positive, the price p_j of any product j produced by firm f must satisfy the first-order condition for profit maximization:

$$s_j(p) + \sum_{k \in \Re_f} \left(p_k - mc_k\right) \frac{\partial s_k(p)}{\partial p_j} = 0 \tag{5}$$

The J equations of all the first-order profit-maximizing conditions for the J products for multi-product firms can be rearranged into the vector of product markups:

$$p - mc = -\Omega(p)^{-1} \times s(p) \tag{6}$$

where p is the $J \times 1$ vector of product prices, mc is the $J \times 1$ vector of product marginal costs, $\Omega(p)$ is the element-by-element multiplication of the $J \times J$ matrix of share price derivatives

$\frac{\partial s_k(p)}{\partial p_j}$ and the $J \times J$ ownership structure matrix, and $s(p)$ is a $J \times 1$ vector of product market shares. Each of the (i, j) elements of the ownership structure matrix equal one when products i and j are produced by the same firm and zero otherwise.

The estimated demand parameters from equation 1 can be used in equation 2 to calculate $s(p)$ and $\Omega(p)^{-1}$. Given actual prices p from the sample data, $s(p)$ and $\Omega(p)^{-1}$, equation 6 can be solved for marginal costs. Given $s(p)$, $\Omega(p)^{-1}$ and marginal costs, equation 6 can be solved again for the prices in equilibria without and with the infringing product characteristic, respectively. With the baseline and new equilibria prices and market shares calculated, the change in profits due to the patent-infringing product characteristic under consideration is:

$$\Delta\pi = \pi(p^N, mc^N, s^N, M \mid x^N) - \pi(p^B, mc^B, s^B, M \mid x^B) \quad (7)$$

where N indicates the value for the relevant economic variables in the new equilibrium and B their value in the baseline equilibrium. Marginal costs have been superscripted in equation 7 to allow them to potentially change for infringing firms in the new equilibrium. This flexibility is permitted because it is often difficult to determine whether a firm is actually infringing on a patent and in some cases, the infringement may be unknown and unintended. For example, the infringing firm may be purchasing a key component from the input market, but does not know that the supplier has potentially infringed until after production and sales have occurred.[3]

We investigate several hypothetical scenarios in Section 5 that involve the complete removal of the infringing product characteristic from the product. In practice, legal standards

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[3] Keeley (1999) notes that the input supplier is likely to have contracted for rights to at least some patents relevant to the component it is selling and these patent rights are transferred to component customers through official sales. However, with the existing patent thicket and increased cross licensing between different input suppliers and manufacturers it is not always clear that there is an actual infringement.

may require replacing the infringing characteristic with a second-best substitute and we note that our framework is flexible enough to allow this possibility.

3. Smartphone industry

3.1 Market overview

We apply this patent evaluation method to smartphones. A smartphone is a high-end mobile phone similar to a hand-held minicomputer. It offers a variety of product characteristics for advanced voice, text, multimedia and Internet functionality, and uses an operating system to seamlessly run third-party software known as applications. There are two costs to having a smartphone. One is the cost of the actual phone as indicated by a typical full retail price of about $400. The other is the consumer’s monthly cost, which depends on whether the consumer is buying their phone on an installment plan, and how much data, talk, and text they need from their service provider. The typical service plan for a smartphone is about $50 per month.[4] In contrast, a feature phone is a low-end mobile phone with basic functionality and limited access to applications. The typical price for a feature phone is about $100 and the monthly service plan is often less than $10.

Figure 1 shows the recent rapid growth in smartphone sales and revenue in the United States. According to IDC (2016) there were about 667 million smartphones sold in the United States between 2010 and 2015 with total revenue of $330 billion. These large revenues, for example, $17.5 billion during the June quarter 2015, have created incentives for patent holders to assert their patents for short-run financial rewards or for long-run strategic advantages

[4] The structural error term ξ_{jt} in equation 1 represents the deviation of unobserved demand shocks from the quarter and firm brand name. These include promotions, quality of service, and the price, quality and incentives of the service plan from the cellular data service provider. In Section 4, we use non-linear GMM with instrumental variables to control for the potential effects of these unobserved characteristics on price.

(Armstrong, et al., 2014; IDC, 2016). The convergence of different voice, data and multimedia technologies, which were previously in separate devices, has also led to increased competition between firms that historically supplied goods in different markets. For example, Ericsson, Motorola and Nokia are traditional telecommunications companies now facing competition from computing companies such as Apple, Microsoft and Sony. This competition has resulted in frequent assertions of declared standard essential patents by the traditional companies, which have a large stock of patents. The new entrants, in turn, have largely asserted patents that cover technologies on computer-driven features and new forms of design that were not present in older mobile devices (Armstrong, et al., 2014). RPX Corp. (2011) estimate that there are about 250,000 current patents relevant to the smartphone which provides a large number of potential infringements for rivals inside the market and non-practicing entities outside the market.

3.2 Sample data

We estimate consumer demand with quarterly data on United States smartphone sales, prices and product characteristics from IDC (2016). The data are aggregated to the product level across 22 national markets ("quarters") from March 2010 to June 2015 initially giving rise to 3,346 distinct product-market observations. Our starting assumption is that the consumer's outside option is to purchase a feature phone. The market share for each smartphone product j in market t (s_{jt}) is therefore the quarterly unit sales of that particular product divided by the quarterly market size (M_t), where market size is the sum of total smartphone sales and total feature phone sales.

PRICE (p_{jt}) is the average price that retailers pay to the smartphone supplier or sales revenue divided by number of units sold, adjusted for inflation with the consumer price index.

The product characteristics in the vector x_{jt} are *STORAGE*, *SCREEN SIZE*, *CPU*, *CORE*, *MEGAPIXELS*, *PIXEL DENSITY*, *BATTERY*, *4G*, *NFC* and *AGE*. *STORAGE* is the storage capacity of the smartphone in gigabytes (GB), *SCREEN SIZE* is the diagonal measure of the smartphone's display area in inches, *CPU* is the speed in gigahertz (GHz) of the central processing unit (CPU), *CORE* is the number of processors in the CPU, *MEGAPIXELS* is the number of megapixels in the smartphone's camera, *PIXEL DENSITY* is the number of pixels per square inch of screen size, *BATTERY* is the number of hours of talk time supported by the battery, *4G* equals one when the smartphone is fourth-generation (4G) compatible and zero otherwise, *NFC* equals one when the smartphone has near field communication and zero otherwise, and *AGE* is the number of quarters since the product's release date.

Some product characteristics in the sample are recorded as a band, for example, "1GB – 4GB" for embedded memory band (*STORAGE*). Since estimation of demand requires a single value, we assigned the midpoint of the band as the value to *STORAGE*, *MEGAPIXELS* and *CPU*. Data on battery life, pixel density and the number of quarters since the product's release are not reported in the underlying data from IDC. We obtained these data directly from third-party websites, such as www.GSMArena.com, www.PhoneArena.com, and www.Specout.com, who in turn gather this information mainly from the web sites of manufacturers.[5]

3.3 Summary statistics

The sample of smartphones includes 655 different products from 35 firms over 22 quarters. On average, each firm sells about seven different products per quarter. Table 1 presents summary statistics. Average quarterly sales are 199,304 for each product with an

[5] Accessed on 5/20/2016.

average price of about $369. On average, storage capacity was 11.14 GB, screensize was 4.067 inches and CPU speed was 1.168 GHz. The number of megapixels in a smartphone's camera was 8.308, the number of pixels per square inch of screen size was 262.2, the number of hours of talk time supported by the battery was 10.7, and the number of processors in the CPU was 2.115. About 42 percent of smartphones have 4G capability and about 31 percent have NFC. The average number of quarters since the release date for phones in our sample was 2.733. Columns two through four show there is substantial variation in prices and characteristics across phone products. For example, prices range from $13 to $987, storage capacity ranges from 0.001 to 128 GB, screen size from 2.2 to 6.3 inches, and CPU speed from 0.5 to 2.3 GHz.[6] This variation indicates that individual smartphones are not the same, and that the manufacturers are differentiating their products for consumers who do not view them as perfect substitutes.

The release dates for new products follow a pattern which may be expected for an industry where technology, on occasions, can change reasonably rapidly. A smartphone is most often released into the highest price category it will ever reach, and steadily falls in price and status as time on the market increases. The highest class of phone, or what Fan and Yang (2016) call a "flagship" smartphone, is usually equipped with the latest technologies, typically sold globally, and is released into one of the highest price brackets. "Non-flagship" phones may start their product life with components and characteristics that are inferior to flagship phones and have relatively lower prices.[7] The downward price trajectory is similar for flagship and non-flagship phones, but with longer sales lifespans for those phones with a higher initial price.

[6] Just under two percent of the sample have prices below $50. This could be due to deep discounting of the price retailers pay to the supplier for older smartphones or it could be recording error. For robustness, we estimated demand with these observations excluded and the results, not reported, are similar to those reported in Table 4.
[7] IDC (2016) classify smartphones into: ultra-low end ($99 or less); low-end ($199 or less); mid-range ($399 or less); high-end ($599 or less); and ultra-high end (more than $599).

Flagship phones are often replaced by a newer version, for example, a new edition of the Samsung flagship, the Galaxy, is released each year in our sample. This new version does not necessarily eliminate sales for the previous versions, but rather the older version is often sold at a lower price as a non-flagship phone for a number of quarters following replacement. For the 426 smartphone products in our sample where we observe every quarter in which it is sold, the average period of sales is 5.16 quarters with a standard deviation of 2.7 quarters. The Blackberry Bold and Apple iPhone 4 were the longest selling phones in our sample, with sales in 14 consecutive quarters.

Firms regularly release new smartphones. On average we observe the entry of 24.6 new products per quarter. Some of this market entry is for entirely new products, but often more established products will be replaced with a newer version, where releases of a new versions are often done on a regular schedule. As an example, Apple has had a primary release of the iPhone, often with several variants, once a year since 2007. We observe 23.3 product exits per quarter in our sample, as old products exhaust demand and are retired in favor of the newer versions. As the amount of time since release increases the price of a products tends to decrease. Figure 2 shows this price trend, adjusted for inflation, as a percentage of its initial price as the smartphone ages. While many firms do not change the opening price of their flagship products, the data show that the relative price of a phone changes. Therefore, a price increase in a newer product may be considered to be a relative change that comes from a decrease in the price of an older phone product.

Lou et al. (2011) and Gowrisankaran and Rysman (2012) argue that a dynamic consumer demand model may be appropriate for products such as digital cameras and camcorders when consumers compare their current product with future products with potential for dramatically improved functionality and rapidly declining prices. Market evidence suggests that smartphones lean toward a consumer non-durable. First, the industry estimates a replacement cycle of between 18 and 24 months.[8] Second, smartphones do not have the physical durability of other consumer electronics such as televisions, audio equipment, cameras and home appliances. When new smartphone products are introduced they are regularly upgraded with improved product characteristics. Table 2 shows an upward trend in storage capacity, screen size, CPU speed and efficiency, and camera quality from 2010 to 2015, but the average age for a smartphone has remained relatively stable at approximately nine months, indicating regular consumer turnover. Given this evidence, we assume static consumer demand for non-durable smartphones and estimate patent damages from short-term profits.[9] However, recognizing that this assumption may not hold perfectly, we follow Lou et al. (2011) by including *AGE* in our demand specification. This controls for the option value from waiting for future products and helps alleviate the potential positive bias on the price coefficient from forward-looking consumer behavior.[10]

The number of firms inside the United States smartphone market is reasonably stable over our sample period. While we do observe some firm entry and exit, the firms involved never manage to obtain a significant share of the market. There are 16 firms that enter the market between 2010 and 2015, three of which exit before the end of the period, with seven exits in total. Of the entrants, the average quarterly market share is 1.12 percent, and no single firm

[8] See http://us.kantar.com/tech/mobile/2016/the-future-of-smartphone-sales-growth/.

[9] Specifically, consumers do not consider future changes in prices in current decisions. A dynamic demand model along the lines of Gowrisankaran and Rysman (2012) may be more appropriate for digital cameras and camcorders where demand is a function of its price and product characteristics, and the expected utility from purchasing new products supplied in the future with improved functionality and dramatically lower prices.

[10] Fan and Yang (2016) assume static demand in their study of product proliferation in United States smartphone markets. Wang (2017) also assumes static demand in his study of product life cycles in Chinese smartphone markets, and includes a flexible specification of the outside good to control for heterogeneity in the quality of consumer's current smartphone over time.

achieves a share greater than 6.48 percent in a quarter. The collective market share of the entrants averages 8.8 percent over the periods in which at least one is in the market, with a maximum of 13.5 percent. Collectively, the entrants never reach the average market share of the third largest firm in the market.

Table 3 presents the top eight firms in the United States during the sample period with collective sales of over 90 percent of the market and total revenue of about $280 billion. Apple and Samsung are the dominant players with relatively high sales volumes and prices per unit each quarter, and with older average product ages. During the second quarter of 2015, the most recent quarter in the data, Apple's market share, average price and revenue were about 38 percent, $699 per unit, and $9.57 billion, respectively. Samsung's share, price and revenue were about 23 percent, $558 per unit, and $4.65 billion, respectively. In contrast, the next biggest player, LG Electronics, had share, price and revenue of about 14 percent, $224 per unit, and $1.17 billion, respectively. The large revenues from the sale of high-end phones make the two dominant firms, Apple and Samsung, a potentially attractive target for patent holders looking to assert the value of their patents.

Another interesting feature from the data is that 4G and NFC compatibility, two of the more advanced standards for wireless communication, are more likely for high-end phones with prices of $400 or more. Cellular functionality is implemented in the baseband processor of the smartphone. The leading 4G cellular standard is Long Term Evolution (LTE) which provides faster upload and download speeds for Internet connectivity and improved quality of sound relative to third-generation (3G) compatibility.[11] About 57 percent of high-price smartphones in

[11] The theoretical maximum download speed for LTE is 100 megabits per second (Mbps) and the maximum upload speed is 50 Mbps. 3G has maximum download and upload speeds of 7.2 and 1.4 Mbps, respectively (http://www.wirelessinternet.org/4G-network.php; http://www.tested.com/tech/smartphones/1630-cdma-vs-gsm-examined-which-3g-network-is-superior/). Typical speeds are lower and vary by network configuration, service

our sample have 4G compared to 31 percent for low-price phones. NFC functionality, which is likely implemented in a "combo chip" that supports several communication functions such as Wi-Fi, Bluetooth and GPS, permits short-range contactless communication between various devices, such as smartphones (Armstrong et al., 2014). It can be used for in-store payment applications like "mobile wallet", for bumping phones to share games, photos and videos, etc., and to synch up with a personal audio system. About 48 percent of high-price smartphones have NFC compared to 19 percent for low-price phones. Given its increasing popularity in cellular devices, particularly in the high-end smartphones supplied by Apple and Samsung, one can expect that there will be increased focus on NFC licensing and litigation in the future (Armstrong et al., 2014, IDC, 2016).

4. Demand estimates

4.1 Estimation and instrumental variables

We estimate demand by applying BLP's GMM estimator to the sample moment condition implied by equation 4. Following standard practice in the literature, we choose cost shifters and BLP-type product characteristics of the other products from the same firm and rivals as the instruments for price. The identification of the demand parameters in consumer utility comes from the variation in consumer choices across the different choice sets supplied by firms. The key assumption is that the cost shifters are exogenous to consumer preferences and that the product characteristics within the choice sets are exogenous to unobserved demand shocks. The

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provider, time of day and year and consumer location. Monthly Ookla data from February 2013 to March 2015 indicate an average download speed of 8.3 Mbps, ranging from 2 to 13.7 Mbps, and an average upload speed of 3.7 Mbps, ranging from 0.7 to 8.2 Mbps. See http://www.ookla.com/speedtest-intelligence.

standard argument for BLP-type instruments is that firms make decisions about their product characteristics before observing the demand shocks.

The cost shifters are *Q_PROCESSOR* (equals one when the manufacturer uses a Qualcomm processor in the smartphone and zero otherwise) and *V_PROCESSOR* (equals one when the manufacturer uses their own processor in the smartphone and zero otherwise). Qualcomm processors are typically more efficient than smartphone manufacturer's processors so *Q_PROCESSOR* is expected to be negatively correlated with price through the price-cost markup equation 6 and *V_PROCESSOR* is expected to be positively correlated. Due to collinearity with the time fixed effects, we had little initial success identifying consumer demand with the typical BLP instruments used in the literature. These include the sum and average of product characteristics for all other products produced by the same firm, and the sum and average of product characteristics for all other products produced by rivals. We overcome these problems by using the deviation from the average of the characteristics for all other products produced by the firm in a given market (quarter). By the argument above, these instruments are correlated with prices through the price-cost markup and not correlated with unobserved utility, unless consumers have a social preference for individualism or conformism and this is revealed to firms when selecting the location of their product characteristics (Akerlof, 1997, Shy, 2001).

4.2 Results

Table 4 presents the demand estimates for equation 1. It is possible that products with unusually low sales are outliers, so we estimated utility on a sample of products with 100 or more unit sales per quarter. We also excluded some relatively older products with second-generation (2G) network compatibility. The final sample for demand estimation is 3,289 product-market observations. Although they are not reported, all model specifications include brand fixed effects ($\lambda_{f(j)}$) and time fixed effects for each quarter in the sample (γ_t).

Columns one and two of Table 4 report ordinary least squares estimates with fixed marginal utility coefficients ("Logit–OLS"), columns three and four report GMM estimates with fixed marginal utility coefficients ("Logit–GMM"), and columns five and six report BLP estimates with random coefficients on *STORAGE* and *CORE* ("RCL–BLP").[12] The market data fit the demand specifications reasonably well as judged by the signs of the estimated marginal utility coefficients. The marginal utilities for most non-price product characteristics are positive and the marginal utility for price is negative.[13] The estimate of price in the Logit–OLS specification in column one is relatively small in absolute terms and this estimate becomes larger as the potential endogeneity of price is controlled for with instrumental variables in columns three and five. This finding is consistent with smartphone prices being positively correlated with unobserved demand shocks.

Because it is the most general specification and controls for the endogeneity of price, we concentrate our demand discussion on the RCL-BLP model in columns five and six.[14] The standard deviations on the random coefficients are large when compared to their mean marginal utility coefficients suggesting that tastes for smartphone storage and CPU cores vary in the

[12] An F statistic for the joint significance of the eight excluded instruments in the first-stage regression of price on all exogenous variables and instrumental variables indicates that the excluded instruments are relevant. The Hansen J statistic cannot reject the null of zero correlation between the instruments and errors and indicate that the instruments are valid. The excluded instruments are the two cost shifters and the transformed demand variables *STORAGE*, *SCREEN SIZE*, *CPU*, *CORE*, *4G* and *NFC*.
[13] We apply the log transformation to price in all demand specifications so that the price sensitivity of consumers is less elastic for high-end smartphones. For robustness, we also estimated demand with linear price. The results, not reported, are qualitatively similar to those reported in Table 4, but produced lower markups in the profit simulations.
[14] The RCL-BLP specifications are estimated with 1,000 Halton draws to approximate the market share integrals. We estimated alternative specifications with additional random coefficients on product characteristics other than *STORAGE* and *CORE*. Their standard deviations were imprecisely estimated and/or the models did not converge so these specifications are excluded from the demand analysis.

consumer population. Some population segments may prefer more storage capacity so that they can conveniently keep and post more photos, songs and other files to and from their smartphone, while other consumers may dislike more storage due to privacy concerns. Similarly, some population segments may prefer more CPU cores for increased processing speed and efficiency, while others may be concerned that they will use their phone more and inadvertently exceed the data limits on their monthly service contract.

The WTP calculations for the non-price product characteristics have signs and magnitudes that conform to *a priori* expectations. All other things held constant, the representative consumer is willing to pay \$98.68 (standard error (s.e.) = 8.86) for an additional inch of screen size, \$9.89 (s.e. = 1.05) for an additional megapixel of camera resolution, \$64.12 (s.e. = 8.48) for 4G compatibility, and \$87.23 (s.e. = 11.20) for NFC. There is a large premium for the dominant firm's brand with the representative consumer willing to pay \$687 (s.e. = 86.86) for an Apple smartphone. These estimates are consistent with other studies of smartphones. For United States markets, Fan and Yang (2016) estimate marginal WTPs of \$143 for screen size and \$12 for camera resolution, and an Apple premium of about \$390. Sun (2012) estimates a WTP for 3G compatibility of \$41 and an Apple premium of about \$381. For Chinese markets, Wang (2016) estimates a much larger brand value for Apple over Oppo, Xiaomi, and Samsung, etc.

4.3 Alternative demand specifications

For robustness, we estimated the RCL–BLP model of demand under several alternative assumptions with the results reported in Table A1 of the Appendix. The demand results in columns one and two are from an expanded sample that includes products with less than 100 sales per quarter and products with 2G compatibility. There is some debate among telecom analysts about whether a phablet device is a smartphone and whether WiMAX smartphones are truly 4G. The demand results in columns three and four include a phablet dummy variable as additional product characteristic, and the results in columns five and six use an alternative measure of 4G compatibility that excludes WiMAX smartphones. Following Nevo (2000), we test the sensitivity of our demand results to an alternative definition of market size and the outside option. Columns seven and eight present results where market size is the total number of cellular connections in the United States, and the outside option is not to purchase a smartphone (Cellular Telecommunications Internet Association (CTIA), 2016; eMarketer, 2016). For a final check, we include both *AGE* and AGE^2 in our demand specification to control for the option value of waiting for future products with the results reported in columns nine and ten.[15]

Overall, the results from the alternative demand specifications are similar to our preferred RCL-BLP results reported in Table 4, which suggests that they are reasonably robust. The next section uses these results in the supply-side to recover marginal costs and to simulate firm profits under Bertrand competition.

5. Simulations

5.1 Market structure

We simplify the simulation of firm profits by assuming there are eight firms supplying smartphones in the June quarter of 2015, the last quarter of our sample. We chose these firms because they account for over 90 percent of actual sales and because the market share of the 9th

[15] We estimate demand over 22 quarters because this data has complete information on smartphone characteristics. For robustness, we also estimated demand with the first two quarters omitted, and again with last two quarters omitted. The results are qualitatively similar to the full sample demand estimates reported in Table 4.

firm is often below one percent.[16] For each of these firms, we identify a primary and secondary smartphone to replicate their flagship and non-flagship products, respectively, in a multi-product setting. The flagship phone is the product with the most sales of high-end phones with a price of $400 or more. When the firm sells no high-end phones, or if a phone in a lower price category generates more revenue, then the flagship is selected from their mid-range and low-end products. The secondary (or non-flagship) phone is the product with the greatest revenue from the middle-range products with prices above $199, but below $400. Table 5 lists the smartphone product names, market prices, market shares and product characteristics for the 16 smartphone products used in our simulation.

The two products for each firm represent the complete product line for each of the multi-product firms in the simulations. We attribute each firm's entire market share to these two smartphones by using the within-firm relative share of each product. For example, if the flagship phone generated 70 percent of the sales observed for the two representative products of a firm (leaving 30 percent to the secondary phone) with ten percent total market share, then the flagship will receive 70 percent of the firm's overall market share; in this case, seven percent of the total market. The non-flagship phone will receive the remaining 30 percent, or three percent of the total market. While somewhat simplified, we think this accurately reflects key aspects of the market structure of the smartphone industry in terms of the number of important manufacturers, multi-product supply, market share, and prices.

Brand fixed effects are included in the demand specification to account for the average market demand from unobserved factors among the different firms. However, because they are estimated for the entire sample period and our simulation is for the most recent period in the

[16] For robustness, we simulated profits for the top nine and top seven firms, respectively, and calculated patent damages that are very similar to those reported in the paper.

data, these constants require recalibration to the second quarter of 2015. Following Train (1986), we recalibrate the brand constants according to:

$$\lambda^{1}_{f(j)} = \lambda^{0}_{f(j)} + ln(s_j / \hat{s}^{0}_{j}) \tag{8}$$

where $\lambda^{0}_{f(j)}$ is the original estimated value for $\lambda_{f(j)}$ in equation 1, $\lambda^{1}_{f(j)}$ is the first adjusted value, s_j is the actual market share observed in the data and $\hat{s}^{0}_{j}$ is the demand model's initial predicted market share before adjustment. Because each firm has two products in the simulation, the new constants are calculated to be specific to the flagship or non-flagship product, adjusted for the difference in shares from the observed market share. For example, if the flagship phone is assigned 70 percent of the firm's market share in the quarter, but the estimate in equilibrium is 65 percent, the five percent difference in the natural log of shares is added to the phone's constant. This is done through an iterative process, where the constant is corrected after simulation, the share is re-estimated, and the correction repeats. We run 20 iterations for each correction in our model, as we find this is sufficient to remove any significant difference between the simulated and actual market shares.

Given prices and estimated demand parameters, we first solve equation 6 for constant marginal costs with the market structure described by Table 5. We assume constant marginal costs based on commentary by industry insiders and technology websites. Analysts suggest that cost advantages are achieved at scale where input pricing for components is discounted in bulk. We can imagine a scenario where a manufacturer facing unexpectedly high demand may have to employ additional suppliers, and marginal costs increase from the unexpected contract. During normal operations, however, we expect the constant marginal cost assumption will hold.[17] The

[17] See http://www.cnbc.com/2015/09/30/apple-iphone-6s-plus-costs-236-to-make-sells-for-749.html, http://www.zdnet.com/article/heres-how-much-the-iphone-7-costs-to-make/, and

last two columns of Table 5 report recovered marginal costs and own-price elasticities of demand for the 16 smartphone products that will be used in our simulations. The own-price elasticities of demand range from –2.702 to –3.917 and imply markups of around 25 to 35 percent. These are similar to the estimates of market power for camcorders by Gowrisankaran and Rysman (2012) and for the wireless industry by Cullen et al. (2016). Marginal costs also seem plausible for most products. For example, our cost estimates for Apple's iPhone of \$302 to \$352 are close to industry breakdown calculations of \$227 to \$288, and our cost estimates for ZTE of \$148 to \$171 are also close to industry calculations of about \$184 (Sherman, 2013; Techinsights, 2016).[18] The one potentially uneasy feature of the baseline results is the relatively high marginal costs for the flagship smartphones of HTC and Motorola.

5.2 Patent infringement

The economic model in the counterfactual analysis can flexibly accommodate a patent holder that is inside or outside of the market, any individual product characteristic, and either single- or multi-firm patent infringers. We include several scenarios below as examples of the potential to calculate patent value with this method.

The first scenario illustrates the potential profits earned by a single dominant firm, in this sample, Apple, when infringing on the NFC patent held by a third-party non-practicing entity outside of the market. NFC functionality is first removed from all phones in the market and prices, shares, and profits are calculated. The removal of NFC from any smartphone that has the

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http://www.recode.net/2014/9/23/11631182/teardown-shows-apples-iphone-6-cost-at-least-200-to-build for examples. Last accessed on 11/23/2016.

[18] The referenced industry cost estimates are for production of the phone where our implied marginal cost estimates would also include shipping and administrative costs.

technology in the actual marketplace is assumed to decrease marginal cost by $12.[19] NFC functionality is then added to Apple's flagship smartphone in violation of the patent, and the new equilibrium prices, shares and profits are calculated. Of the two Apple phones chosen for the second quarter of 2015 only the flagship has NFC technology, so it is the only phone to receive the infringing characteristic in this counterfactual. Table 6 reports the results from this simulation and shows that market share increases by 9.6 percent for the Apple flagship phone, but decreases by about 4.4 percent for the non-flagship phone which is less attractive to consumers relative to Apple's flagship. Apple's total profits increase by $1.37 billion from the addition of NFC functionality with the large gain for the flagship mitigated slightly by a small loss in profits for their non-flagship phone without NFC. Overall, profits for the dominant firm's products with NFC increase on average by 26 percent per smartphone, or an average of $52 per phone sold, during the second quarter of 2015 when compared to the alternate scenario where none of the top eight firms use NFC technology. This estimate provides a starting point for establishing a reasonable royalty between the patent holder and the dominant firm in a hypothetical negotiation over the legal use of NFC technology.

Because they fall further behind the dominant firm's improved technology, the other seven firms inside the market are also impacted by Apple's infringement and collectively lose $200 million in profits and three percent market share. Samsung and LG, the next two largest firms in the market, are affected the most, losing $83 and $41 million respectively. This interesting result shows how law-abiding firms inside the market can also be damaged by the "anti"-competitive (patent infringing) behavior of the dominant firm. Overall, total profits for

[19] Industry estimates range from $3 to $23 with a mid-point of about $12 to $13. We also tested marginal cost reductions of $3 and $23, respectively, and obtained qualitatively similar results.

the eight firms increase by $1.17 billion and they collectively gain about two percent market share from the outside option, with all of the gains accruing to the dominant firm.

Table 7 presents the results from a second scenario where the dominant firm inside the market is the holder of the NFC patent and the second largest firm, Samsung, infringes. In contrast to the first scenario, this represents a situation where the patent holding firm inside the market could potentially lose profits because of the patent infringing behavior of a rival.[20] In this scenario, Apple loses $353 million with most of this loss attributed to a reduction in the margins for both of their products. These lost profits provide a measure of the compensatory damages to the patent holder as a result of the patent infringement on NFC technology.

As an interesting aside, Samsung's margins increased dramatically when NFC functionality is supplied on their smartphone products and their profits increase by 80 percent. This is not surprising since Samsung is a large player in the market and NFC availability on its phones reduces the competitive advantage of the dominant firm. The other six firms in the market collectively lose $202 million from Samsung's infringement with most of their losses arising from lost market share rather than large reductions in margins.

5.3 Survey-based preferences

Horsky et al. (2006) and Goldfarb et al. (2009) note that survey-based estimates of consumer preferences can also be a useful input into the utility function used for equilibrium profit simulations. For example, in our demand model we cannot estimate precisely the separate marginal utilities for storage capacity and memory card access, respectively, because these two

[20] For example, in Apple v. Samsung (2012), Apple claimed the patents over smart gestures and certain design features in smartphones and sued Samsung. Apple argued that Samsung infringed upon these patents and reduced Apple's profits from what they would have been absent the infringement (Hauser, 2012; Allenby et al., 2014).

characteristics are highly collinear in the market data. However, we do have a conjoint estimate of the marginal utility of *MEMORY SLOT* (equals one when the smartphone has a slot for memory cards that support additional capacities, and zero otherwise) from a pilot test of 100 survey respondents in a previous study. We include this conjoint estimate of marginal utility, which is approximately valued at $40, as an additional preference parameter in our demand model and repeated scenarios one and two described above. The results from these scenarios, not reported, are qualitatively similar to those reported in Tables 6 and 7, but with the prices and profits slightly higher for smartphones with a slot for memory cards.[21] These findings suggest that our estimated demand specification, described by equations 1 and 2, is reasonably robust and, if required, could be used to simulate the profit effects from an infringement on a patented characteristic that is not readily measured by aggregate market data.[22]

5.4 Breach of contract

The valuation method employed in this paper can also be applied to the calculation of damages in a breach of contract case. We consider a scenario where a component supplier fails to deliver a properly functioning input, such as a cell phone battery that tends to overheat and explode with excessive use. Because the smartphone firm has a faulty product and may suffer a reduction in brand value, they may want to sue the component supplier for breach of contract.[23]

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[21] Results available by request.

[22] Conjoint analysis may also be preferred when the patent permits a measurable improvement in the infringing characteristic already supplied on the product. For example, market data measures whether a phone is supplied with or without 4G functionality, with this functionality implying maximum theoretical download and upload speeds for online activities. These data cannot estimate the marginal utility of a small increase in the typical speed experienced by consumers as a result of patented software process that complements 4G functionality. Conjoint analysis, however, can vary typical speeds with an experimental design that identifies this marginal utility parameter.

[23] Faulty products and recalls are frequent in smartphone markets. For example, Apple recalled some iPhone 5 phones because they suddenly experienced shorter battery life or need to be charged more frequently. Consumers have also reported that when physical pressure is applied to an iPhone 6 or 6 Plus, it may bend.

In the spirit of Goldfarb et al. (2009) and Sun (2012), we use our model to estimate the likely damages to the smartphone firm from such a scenario.

For illustrative purposes, assume a breach of contract for the second largest firm in the market, Samsung, which has an estimated brand value of $293 (s.e. = 59.55) per smartphone from our market demand estimates in Table 4. Further, assume that a consumer survey reveals a loss in confidence in the Samsung brand of 15 percent due to the malfunctioning battery. We degrade the Samsung brand by this amount through a reduction in its estimated brand-specific fixed effect. We then calculate the new equilibrium prices, shares and margins under this brand degradation scenario and compare them to the firm's prices, shares and margins without this degradation, initially reported in Table 5.

The results from this scenario in Table 8 show that Samsung has moderate price reductions, but loses substantial market share of 5.2 percent. Their resulting lost profits of $463 million provide a measure of the potential compensatory damages owed by the component supplier to Samsung for breach of contract.[24] We also note that the decline in Samsung's brand permits Apple to increase profits by $199 million and permits the other six firms to collectively increase profits by $109. Interestingly, most of the firm's price increases besides Apple are less than one percent, and several firms reduce prices on some of their products to capture more share. These firms gain enough market share so that the top eight firms collectively lose very little to the outside option as a result of Samsung's decline in brand value.

[24] The Harris Poll 2016 Reputation Quotient Rankings placed Samsung 49th among the United States 100 most visible companies. Given they were ranked in the top 10 for 2013 to 2015, it possible that their exploding handset problem and the arrest of a senior executive on bribery charges has negatively affected the firm's brand in the actual marketplace. See http://www.theharrispoll.com/reputation-quotient.

6. Conclusions

This article described a method for measuring patent value with aggregate market data and the BLP approach and applied the method to United States smartphones. To the best of our knowledge this is the first publicly-available paper to measure patent value in an equilibrium framework from transactions observed in an actual market. Demand estimates and recovered marginal costs were used to produce sensible simulations of equilibria prices and shares from several hypothetical patent infringements. In one simulation, the presence of near field communication on the dominant firm's flagship smartphone results in a 26 percent increase in profits per phone. This estimate provides a starting point for establishing a reasonable royalty between the patent holder and the dominant firm in a hypothetical negotiation for the authorized use of NFC technology.

The underlying economic framework used to measure patent value with market data is standard in the literature, well grounded in economic theory and econometrics, and relatively straightforward to apply. This is particularly advantageous for legal negotiations and settlements where the courts and lawyers work within much shorter time horizons than typical academics. The patent valuation method can also accommodate marginal utility coefficients that are estimated from conjoint experiments to measure the potential damages from a product characteristic that is imperfectly measured with market data. Mixing conjoint and market data in a formal integrated approach along the lines of Brownstone et al. (2000) and Horsky et al. (2006) would be a useful area of future research. Another area of future research is the formal analysis of the legal and economic effects from patent-infringing behavior on the third-party, law-abiding firms inside the market.

The hypothetical scenarios described in this study are for academic interest and we do not suggest that any of the firms are actually infringing on patents or breaching contracts. Finally, while the static oligopoly model underlying our analysis can be implemented in a timely manner to produce credible first-order estimates of economic values, researchers must be ready to defend assumptions about static versus dynamic demand, dynamic pricing, and firm entry and exit. Like all models in industrial organization, law, and regulation, this is done on a case-by-case basis.

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Appendix: Table A1. RCL-BLP results from alternative demand specifications

	Expanded sample		With Phablet control		WiMAX as 3G		Different outside option		With *AGE*^{2}	
	MU	s.e.	MU	s.e.	MU	s.e.	MU	s.e.	MU	s.e.
CONSTANT	9.9934***	2.9295	8.1701***	3.1423	7.7450***	2.9295	6.5199*	3.4781	8.5285***	3.1024
STORAGE										
Mean	-0.0372***	0.0044	-0.0760***	0.0050	-0.0725***	0.0048	-0.4053***	0.0083	-0.0698***	0.0049
S.D.	0.0516	0.0493	0.0832*	0.0440	0.0798*	0.0418	0.2034*	0.1107	0.0781*	0.0433
SCREEN SIZE	1.1353***	0.1533	1.1457***	0.1502	1.0144***	0.1481	1.3831***	0.1767	1.0778***	0.1538
CPU	0.8252***	0.1711	1.0395***	0.1779	1.0096***	0.1691	1.7769***	0.2118	1.0417***	0.1743
CORE										
Mean	-0.0387	0.0381	-0.1234***	0.0412	-0.0448	0.0390	-0.5385***	0.0560	-0.0875**	0.0405
S.D.	0.3615	0.3084	0.4488	0.2955	0.3517	0.3021	0.5484	0.3896	0.4148	0.2961
MEGAPIXELS	0.1119***	0.0193	0.1078***	0.0199	0.1032***	0.0190	0.1414***	0.0232	0.1062***	0.0193
PIXEL DENSITY	0.0087***	0.0013	0.0094***	0.0013	0.0090***	0.0013	0.0137***	0.0015	0.0093***	0.0013
BATTERY	0.0185**	0.0089	0.0241***	0.0087	0.0212***	0.0087	0.0219**	0.0111	0.0213**	0.0088
4G	0.6373***	0.1542	0.6818***	0.1641	0.6322***	0.1456	0.9133***	0.1881	0.6800***	0.1578
NFC	0.9017***	0.1339	0.9603***	0.1349	0.9239***	0.1312	1.3373***	0.1604	0.9534***	0.1340
AGE	-0.0776***	0.0185	-0.0822***	0.0186	-0.0852***	0.0178	-0.0758***	0.0213	-0.0295	0.0347
AGE^2									-0.0054**	0.0026
PHABLET			-0.2039	0.1628						
PRICE	-4.1169***	0.6283	-3.8424***	0.6586	-3.6752***	0.6204	-4.2175***	0.7385	-3.8641***	0.6404
Observations		3,346		3,289		3,289		3,289		3,289
Relevance	$F(8, 3273)$	13.46	$F(8, 3216)$	12.08	$F(8, 3216)$	13.02	$F(8, 3216)$	12.63	$F(8, 3216)$	12.71
Validity	$J[\chi_2(5)]$	4.224	$J[\chi_2(5)]$	3.336	$J[\chi_2(5)]$	5.835	$J[\chi_2(5)]$	1.576	$J[\chi_2(5)]$	4.263

Notes. MU is estimate of marginal utility. s.e. is robust standard error. S.D. is standard deviation. Brand and time fixed effects not reported. *F* tests the significance of first-stage instruments. *J* is Hansen J statistic. Expanded sample includes products with less than 100 sales per quarter and those with 2G. The different outside option is not to purchase a smartphone.

Table 1. Summary Statistics

	Mean	S.D.	Min	Max
MARKET SIZE	4.53E+07	4,923,393	3.69E+07	5.78E+07
UNIT SALES	199,304	405,898	1	4,841,574
PRICE (nominal)	369.22	194.42	13	987
STORAGE	11.14	16.31	0.001	128
SCREEN SIZE	4.067	0.859	2.2	6.3
CPU	1.168	0.482	0.5	2.3
CORE	2.115	1.390	1	8
MEGAPIXELS	8.308	4.682	0	40
PIXEL DENSITY	262.2	86.13	121	577
BATTERY LIFE	10.70	6.372	2.85	48
4G	0.421	0.494	0	1
NFC	0.313	0.464	0	1
AGE	2.733	2.673	0	19

Notes. Number of observations is 3,346, except market size where the statistics are drawn from 22 quarters. S.D. is standard deviation.

Table 2. Evolution of smartphone characteristics 2010 to 2015

	Average for June quarter					
	2010	*2011*	*2012*	*2013*	*2014*	*2015*
STORAGE	2.892	3.831	7.547	10.63	13.07	17.26
SCREEN SIZE	3.015	3.398	3.725	4.066	4.423	4.701
CPU	0.574	0.776	0.990	1.230	1.385	1.460
CORE	1.013	1.064	1.331	1.925	2.572	3.488
MEGAPIXELS	4.635	5.873	7.081	7.925	9.563	10.28
PIXEL DENSITY	207.4	216.7	229.9	262.7	285.8	302.5
BATTERY	5.635	6.043	6.970	9.892	13.12	15.41
4G	0	0.036	0.258	0.575	0.590	0.617
NFC	0	0.027	0.113	0.473	0.488	0.430
AGE	3.180	2.455	2.435	2.719	3.187	3.067
Observations	78	110	124	146	166	326

Table 3. Sales of top eight smartphone firms for second quarter 2015

Firm	*SALES*	*SHARE (%)*	*REVENUE ($b)*	*PRICE ($)*	*AGE (years)*
Alcatel	1,186,900	3.3	0.167	141	0.800
Apple	13,701,986	38	9.574	699	5.640
HTC	916,260	2.5	0.417	455	3.842
LG	5,238,618	14.5	1.174	224	3.271
Motorola	1,305,000	3.6	0.427	327	3.188
Nokia	617,089	1.7	0.087	140	2.833
Samsung	8,336,743	23.1	4.651	558	3.381
ZTE	2,660,566	7.4	0.358	135	3.381
All firms	36,061,509	100	17.24	478	3.067

Notes. Top eight firms in the United States during the sample period. Reported data are for the second quarter of 2015.

Table 4. Demand results

	Logit-OLS		Logit-GMM		RCL-BLP	
	MU	s.e.	MU	s.e.	MU	s.e.
CONSTANT	-5.9591***	0.5820	9.5300***	2.9525	8.6526***	3.0500
STORAGE						
Mean	-0.0096***	0.0016	0.0072**	0.0037	-0.0775***	0.0051
S.D.					0.0847*	0.0441
SCREEN SIZE	0.2444***	0.0682	0.9610***	0.1494	1.1016***	0.1554
CPU	0.2953**	0.1156	0.6117***	0.1641	1.0771***	0.1767
CORE						
Mean	0.1334***	0.0284	0.1016***	0.0341	-0.1282***	0.0417
S.D.					0.4541	0.2978
MEGAPIXELS	0.0048	0.0100	0.0861***	0.0182	0.1104***	0.0197
PIXEL DENSITY	0.0006	0.0006	0.0065***	0.0013	0.0097***	0.0013
BATTERY	0.0058	0.0063	0.0092	0.0082	0.0228**	0.0090
4G	-0.2420***	0.0704	0.4703***	0.1532	0.7158***	0.1560
NFC	0.2967***	0.0762	0.7661***	0.1286	0.9738***	0.1353
AGE	-0.1573***	0.0100	-0.1573***	0.0180	-0.0813***	0.0187
PRICE	-0.4317***	0.0787	-3.8081***	0.6238	-3.9195***	0.6483
Relevance			$F(8, 3216)$	12.63	$F(8, 3216)$	12.63
Validity			$J[\chi_2(7)]$	7.274	$J[\chi_2(5)]$	3.541

Notes. MU is estimate of marginal utility. s.e. is robust standard error. S.D. is standard deviation. Number of observations is 3,289. Brand and time fixed effects not reported. *F* tests the significance of first-stage instruments. *J* is Hansen J statistic.

Table 5. Simulated smartphone products

Firm	Product name	*PRICE*	*STORAGE*	*SCREEN SIZE*	*CPU*	*CORE*	*MEGA-PIXELS*	*PIXEL DENSITY*	*BATTERY*	*4G*	*NFC*	*AGE*	*SHARE (%)*	*MC*	*OPED*
Alcatel	One Touch Idol 3	249	16	5.5	1.5	8	16.5	401	13	1	1	0	2.01	182	-3.739
Alcatel	Pop Mega	249	4	6.0	1.3	4	10.5	184	14	1	0	1	0.75	184	-3.882
Apple	iPhone 6	636	16	4.7	1.3	2	10.5	326	14	1	1	3	24.8	365	-2.702
Apple	iPhone 5	529	16	4.0	1.3	2	10.5	326	10	1	0	7	7.17	304	-3.567
HTC	One M9	655	16	5.0	2.2	8	30	441	22	1	1	1	1.71	468	-3.513
HTC	Desire Eye	359	16	5.2	2.2	4	16.5	424	20	1	1	2	0.45	266	-3.897
LG	G4	585	32	5.5	1.9	6	16.5	538	20	1	1	0	8.01	386	-2.971
LG	G3	245	8	5.5	1.1	4	10.5	294	15	1	0	3	4.15	140	-3.678
Motorola	Moto X	547	32	5.2	2.3	4	16.5	424	24	1	0	3	2.67	402	-3.785
Motorola	Droid Mini	349	16	4.3	1.7	2	10.5	342	28	1	1	7	0.37	257	-3.901
Nokia	Lumia 830	399	16	5.0	1.3	4	10.5	294	15	1	1	2	1.40	295	-3.849
Nokia	Lumia 1320	279	16	6.0	1.7	2	6.5	245	21	1	0	4	0.04	207	-3.917
Samsung	Galaxy S5	522	32	5.1	2.3	4	16.5	432	21	1	1	5	14.0	327	-2.915
Samsung	Galaxy S4	366	16	5.0	1.9	4	16.5	441	17	1	1	8	5.38	241	-3.648
ZTE	Zmax	236	16	5.7	1.1	4	10.5	258	14	1	0	3	4.52	171	-3.692
ZTE	Grand X Max	205	16	6.0	1.1	4	16.5	245	6.5	1	0	1	1.68	148	-3.835

Notes. OPED is own-price elasticity of demand. SHARE accounts for the firm's total market share in the two representative products and is not the true market share of the selected product, but the market share used for simulation.

Table 6. Apple infringes on third-party NFC patent

		No NFC on all phones				Apple has NFC on iPhone 6 (infringing scenario)			
Firm	Product name	Price	MC	Share	Profit (m)	Price	MC	Share	Profit (m)
Alcatel	One Touch Idol 3	$232	$170	1.67%	$43.19	$231	$170	1.55%	$39.85
Alcatel	Pop Mega	$251	$184	1.00%	$28.25	$251	$184	0.88%	$24.89
Apple	iPhone 6	$581	$353	18.62%	$1,798	$648	$365	28.26%	$3,387
Apple	iPhone 5	$515	$304	11.13%	$994.9	$566	$304	6.76%	$750.3
HTC	One M9	$615	$456	1.41%	$94.25	$615	$456	1.34%	$89.59
HTC	Desire Eye	$342	$254	0.31%	$11.37	$342	$254	0.27%	$10.08
LG	G4	$518	$374	9.60%	$620.3	$516	$374	9.13%	$579.9
LG	G3	$250	$128	3.63%	$114.8	$249	$128	3.28%	$101.5
Motorola	Moto X	$551	$402	3.84%	$242.2	$550	$402	3.44%	$214.8
Motorola	Droid Mini	$340	$245	0.21%	$8.62	$339	$245	0.19%	$7.60
Nokia	Lumia 830	$382	$283	0.92%	$38.62	$382	$283	0.82%	$34.23
Nokia	Lumia 1320	$279	$207	0.05%	$1.65	$279	$207	0.05%	$1.46
Samsung	Galaxy S5	$495	$315	10.53%	$781.8	$489	$315	10.02%	$721.3
Samsung	Galaxy S4	$345	$229	3.81%	$184.3	$341	$229	3.52%	$164.9
ZTE	Zmax	$240	$171	6.24%	$183.5	$239	$171	5.65%	$163.1
ZTE	Grand X Max	$210	$148	2.25%	$58.86	$209	$148	2.04%	$52.33

Notes. m is million.

Table 7. Samsung infringes on Apple's NFC patent

		Apple has NFC on iPhone 6				Samsung has NFC on both phones (infringing scenario)			
Firm	Product name	Price	MC	Share	Profit (m)	Price	MC	Share	Profit (m)
Alcatel	One Touch Idol 3	$231	$170	1.55%	$39.86	$231	$170	1.27%	$32.54
Alcatel	Pop Mega	$251	$184	0.88%	$24.89	$251	$184	0.78%	$22.03
Apple	iPhone 6	$648	$365	28.27%	$3,388.0	$632	$353	27.42%	$3,106.0
Apple	iPhone 5	$566	$304	6.76%	$750.4	$550	$304	6.65%	$694.4
HTC	One M9	$615	$456	1.34%	$89.61	$615	$456	1.10%	$73.19
HTC	Desire Eye	$342	$254	0.27%	$10.08	$341	$254	0.23%	$8.60
LG	G4	$516	$374	9.13%	$580.0	$510	$374	7.79%	$474.5
LG	G3	$249	$128	3.28%	$101.6	$247	$128	2.95%	$89.07
Motorola	Moto X	$550	$402	3.44%	$214.8	$548	$402	2.97%	$183.4
Motorola	Droid Mini	$339	$245	0.19%	$7.60	$337	$245	0.17%	$6.71
Nokia	Lumia 830	$382	$283	0.82%	$34.23	$382	$283	0.70%	$29.21
Nokia	Lumia 1320	$279	$207	0.05%	$1.46	$279	$207	0.04%	$1.32
Samsung	Galaxy S5	$489	$315	10.02%	$721.5	$544	$327	14.40%	$1,296.0
Samsung	Galaxy S4	$341	$229	3.52%	$164.9	$381	$241	5.19%	$302.8
ZTE	Zmax	$239	$171	5.65%	$163.1	$238	$171	4.93%	$139.5
ZTE	Grand X Max	$209	$148	2.04%	$52.34	$208	$148	1.79%	$44.79

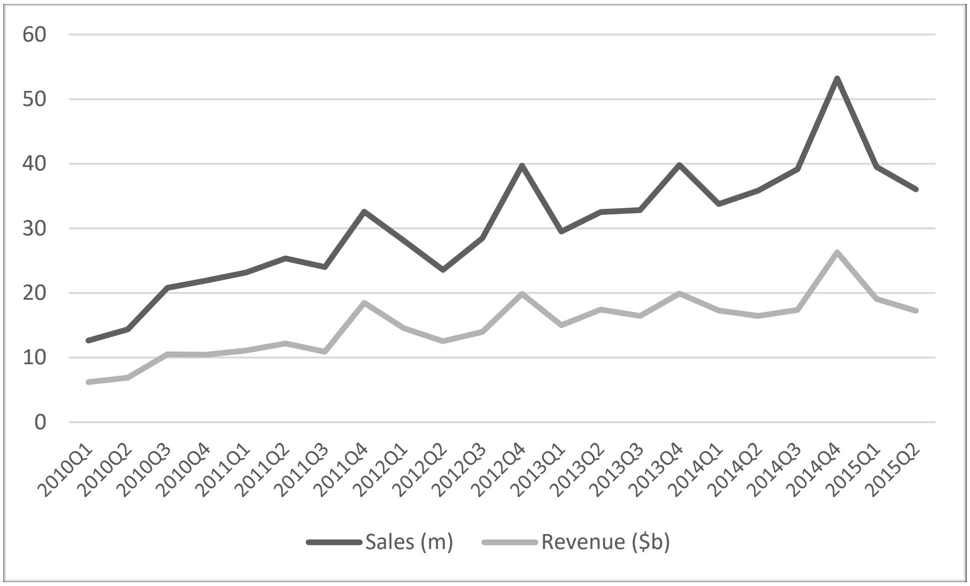
Notes. m is million.

Table 8. Samsung suffers brand degradation from breach of contract

		No brand degradation				15 percent degradation of Samsung brand (breach of contract)			
Firm	Product name	Price	MC	Share	Profit (m)	Price	MC	Share	Profit (m)
Alcatel	One Touch Idol 3	$249	$182	2.01%	$56.80	$248	$182	2.17%	$60.15
Alcatel	Pop Mega	$249	$184	0.75%	$20.50	$251	$184	0.77%	$21.91
Apple	iPhone 6	$636	$365	24.8%	$2,835	$636	$365	26.6%	$3,038
Apple	iPhone 5	$529	$304	7.17%	$682.0	$553	$304	6.44%	$678.7
HTC	One M9	$655	$468	1.67%	$132.3	$631	$468	1.96%	$135.2
HTC	Desire Eye	$359	$266	0.45%	$17.76	$359	$266	0.49%	$19.16
LG	G4	$585	$386	8.04%	$674.4	$550	$386	10.7%	$739.6
LG	G3	$194	$140	4.15%	$94.58	$201	$140	3.84%	$98.26
Motorola	Moto X	$547	$402	2.67%	$163.7	$549	$402	2.85%	$176.5
Motorola	Droid Mini	$349	$257	0.37%	$14.35	$354	$257	0.37%	$15.33
Nokia	Lumia 830	$399	$295	1.40%	$61.12	$400	$295	1.50%	$65.93
Nokia	Lumia 1320	$279	$207	0.04%	$1.250	$281	$207	0.04%	$1.330
Samsung	Galaxy S5	$522	$327	14.0%	$1,149	$506	$327	10.4%	$780.0
Samsung	Galaxy S4	$366	$241	5.39%	$284.5	$360	$241	3.80%	$190.8
ZTE	Zmax	$236	$171	4.52%	$124.8	$238	$171	4.76%	$134.4
ZTE	Grand X Max	$205	$148	1.67%	$40.18	$207	$148	1.73%	$43.16

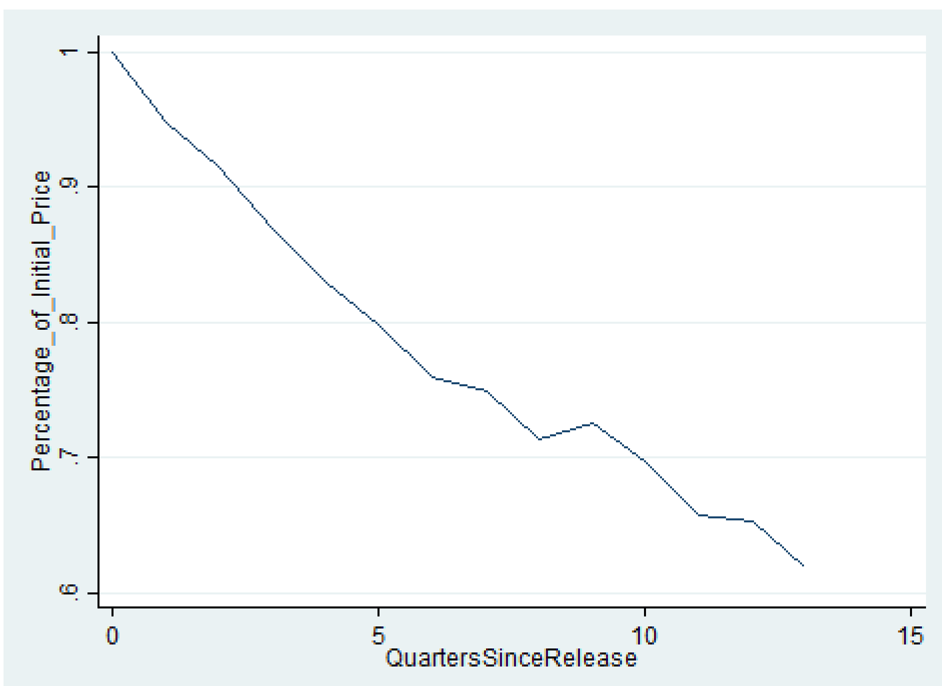
Notes. m is million.

Figure 1. Smartphone sales and revenue 2010 to 2015



Source. IDC (2016).

Figure 2. Smartphone price evolution as a percentage of initial price



Source. IDC (2016).