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An Alternative Framework for Empirically Measuring the Size of Counterfeit Markets
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ABSTRACT

This paper develops a new method for estimating trends in the size of counterfeit markets. The method draws on principles of microeconomic theory and uses aggregated product-level data to estimate counterfeiting activities in various geographic markets. Using confidential firm unit forecasts and actual sales information, a two stage approach is employed that first accounts for unexpected but observable factors that could lead to forecasting error and then, in the second stage, considers the influence of market susceptibility to IPR infringement. Data are analysed for 45 related products sold by a single firm operating in 16 countries during the period 2006-2011. Our models predict larger amounts of counterfeiting in countries with higher corruption norms, lower government control and effectiveness. Predictions of the level of counterfeiting obtained from the second stage are then compared to estimates of counterfeiting derived internally by the firm using shadow-shopping methods. While our two stage model generally under-predicts the level of counterfeiting in each year, it generates trends in counterfeiting that are broadly consistent with those obtained using more costly and intensive methods.

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I. Introduction

As controversy over regional agreements and national legislations heat up in Europe, North America, and Asia over intellectual property rights (IPRs), it is important to take a step back and consider why this has become such a contentious issue and what is really at stake here. IPRs refer to protections granted to firms and/or individuals who are the creators of ideas, products, or methods that allow the creators /inventors a period of time in which they can earn exclusive returns on these intangible and tangible products as a way of rewarding them for the risky investment they initially made to produce the product. These protections, however, are only recognized (and legally enforced) within specific borders defined by the agency granting the IPR (a national government or regional authority, for example). IPRs conferred by one country (e.g. Germany, the U.S.) are not always recognized as legitimate protections by other countries (e.g. China). How to deal with violators of IPRs residing in other countries, therefore, becomes a matter of international policy.

Trends in globalisation and the integration of markets in recent decades seem to have facilitated a rapid spread of violations of these IPRs, namely counterfeiting and piracy. Widespread access to computers, internet and other technological developments that help illicit businesses duplicate designs, labels, logos, packaging and documentation with speed, accuracy and relative anonymity have also contributed to the recent rise (Treverton et al. 2009; Yao, 2005; Alcock et al., 2003). Although counterfeiting began with just a few product groups, such as luxury clothing and personal accessories, it has now spread to a wide range of industries, including those affecting the health and safety of populations (Cheung & Prendergast, 2006; OECD, 2008). Recent estimates of the size of the global counterfeit and piracy market is in the range of $250-$650 billion and growing (Frontier Economics 2011). Counterfeiting as a share of authorised trade in particular has increased by 5.4% from 2000 to 2007 (OECD, 2008).

The protection of IPRs is not a universally accepted idea and debate continues over whether there are positive economic gains from it. On the one hand, intellectual property rights (IPRs) are argued to encourage investment in research and development that lead to further economic growth. Protection of IPRs, therefore, plays an important role in innovation, creativity and competitiveness, and ultimately in economic growth of a knowledge-based economy (GAO, 2010; Grossman and Shapiro 1988). On the other hand, some argue that IPRs generate barriers to entry and slow innovation since some firms cannot enter markets legitimately or smaller firms do not know how nor have the resources to navigate the system and acquire IPRs (Boldrin and Levine, 2002, 2008). What is clear is that by copying and selling unauthorised material, counterfeiters and pirates undermine the role of IPRs and lead to an inefficient allocation of productive resources as legitimate firms and government attempt to deter and punish violators of these patents (Balfour, 2005). At least one study finds limited effects of IPRs on economic growth (Lerner 2009).

To understand whether it is indeed still economically beneficial to grant these rights in an environment where protection of them is becoming increasingly more difficult, one must consider the economic net benefit in a real world setting. While identification and calculation of the economic gains associated with protected production/distribution of intellectual property are easily quantified, one must know something about the lost wealth caused by counterfeiters / pirates who try to steal from these markets (i.e. the size of the illegal market), the public health and safety consequences of substandard counterfeits on the market, and the (public and private) resources dedicated toward reducing these counterfeits/ pirated goods and enforcing IPR protections in order to obtain a true assessment of the net societal benefit and their impact on economic growth and innovation.

This paper focuses its attention on the first component of costs mentioned above: the size of the illegal market. Measurement of the size of any illegal market is always tricky, but models have developed for other informal or “black” markets, including illicit drugs, human trafficking, and firearm trade (Kilmer and Pacula, 2009; Laczo and Gramegna, 2003; Levitt and Venkatesh, 2000; Cook, Moliconi, and Cole, 1995). Many of these models rely on seizure data or self-reported use of illegal items. As such, they remain open to significant criticism by scientists and practitioners. In particular, seizure data is susceptible to variation in levels caused by changes in law enforcement and intelligence rather than a true change in the amount of goods passing through a given border/market. Self-reported consumption data is susceptible to known reporting biases caused by unwillingness to report behaviour that is sensitive or illegal.

A key difference in the case of IPR violations is that these markets operate with legitimate sellers that have legally protected rights which confer economic profits on them, which is why illegal producers move into the market in the first place. As such, economic theory regarding firm behaviour in these legal markets can be used to generate estimates of the amount of illegal sales that are derived from the legal market. While several economic theories have emerged describing these markets and the supply and demand factors that might be important for influencing them, very few have been used to try to estimate the number of counterfeited/pirated goods available on a market and we are not aware of any that have been used to measure the overall size of a counterfeit market.

In this paper we develop and test an empirical model of unmet demand which can be derived from the theory of vertically differentiated products, oligopoly competition, or monopoly supply to estimate the potential size of a single counterfeited market. While some of the unmet demand may be due to broader market factors, such as product or market shocks (e.g. new release of a substitute product from a competitor, break in the supply chain due to an earthquake or tsunami), such factors are known to the firm ex post. The key to this model therefore is to make use of historical product-specific information on forecasts and actuals to obtain unexplained (post-hoc) differences in unmet demand and determine whether country-level policies related to counterfeiting can explain a portion of the remaining amount of unmet demand. We empirically test this theory using proprietary individual firm-level data of a global technology that is widely known to be targeted by counterfeiters. Estimates of the size of counterfeiting (in units) generated from this model are then compared to estimates produced internally by the firm on the level of counterfeits sold using shadow-shopping and survey techniques. Ninety five percent confident intervals are generated around our model estimates and we assess the extent of the time to which the firm's predictions fall within these confidence intervals. Thus we can evaluate the extent to which estimates from our relatively low cost estimation strategy approximate estimates of counterfeiting that are obtained from using the industry's gold-standard.

The main contribution of this study is the development of a broad empirical methodology that can be applied systematically and at relatively low cost annually to multiple firms, products and industries to approximate the size of the counterfeit market and trends in this market. The methodology can therefore be applied by national policy makers, regional policy makers, and/or trade organizations to assess general policies, programs and practices aimed at reducing overall counterfeiting rather than counterfeiting of any particular product or good. While in principle the general model might also apply to pirated goods, we leave it to future work to consider the reliability of this approach vis-à-vis other economic models that have emerged focusing on measuring these markets (see for example Liebowitz 2008; Oberholzer-Gee and Strumpf, 2007; Hui and Png, 2003).

A second contribution of our work is to demonstrate quantitatively how the share of unmet demand for an authorized supplier of a technology good varies with economic, legal and infrastructure constraints. Similar to what has been shown in previous studies, we find that control of corruption and having a strong rule of law are strong deterrents to counterfeiters within a national market, even when the social norms/attitudes about buying illegal goods are held constant through country fixed effects. Thus, policies can be effective at influencing the level of counterfeiting in the market as well as trends. Moreover, we find that countries that have higher levels of international tourism, a correlate with strong demand for national products and one-time shoppers, experience higher levels of counterfeiting.

The rest of this paper is organized as follows. In Section II, we provide a review of the relevant literature pertaining to theories of counterfeiting and estimation of the size of the counterfeit market. In Section III, we structure a model based on Singh and Vives (1984) to develop the analytical implications of deciding outputs. The empirical strategy for estimating the model described is then provided in Section IV. We discuss the confidential firm-level data used to estimate the model as well as source of policy variables in Section V. In Section VI we present our results and we provide conclusions and discuss implications for future methods for estimating the size of counterfeit markets in Section VII.

II. Background Literature on the Counterfeit Goods Market

The counterfeiting literature can be broken into three general strands of work: (1) Studies that attempt to model the behaviour of firms (legitimate and counterfeiters) operating in markets experiencing competition from illegal markets; (2) Studies that attempt to understand and/or model behaviour of consumers in these markets and social welfare[1]; and (3) estimates of the size of the market. All three literatures are relevant to understand the basis for developing a regional or global estimate, as they each bring important insights regarding the unique dynamics of these markets.

Studies on the behaviour of firms. A very large literature exists trying to describe theoretically the behaviour of specific types of firms in markets with illegal competition, all

[1] This presumes that studies focusing on the impact of counterfeiting on price of the authentic good would be included in the literature on social welfare, as social welfare as it is used here refers to changes in consumer surplus, producer surplus, and deadweight loss.

prescribing to the following general description of markets. The vast majority of the theoretical work in this area treats the owners of intellectual property as monopoly sellers, in the sense of having exclusive rights to sell the matter containing the right which limits entry into the market (Bate, Jin and Mathur, 2011; Yao, 2005; Kitsch, 2000; Higgins and Rubin, 1986), although models do exist describing other frameworks including oligopolies (Grossman and Shapiro, 1988) and competitive markets with differentiated goods (Scandizzo, 2001; Shaked and Sutton, 1982, 1983; Gabszewicz and Thisse, 1979). Firms may use a trademark as one way of differentiating their product. However, the more successful a firm is at differentiating its product, the greater the incentive for counterfeiters and pirates to enter that market.

As described in a recent study by Qian (2011), counterfeit sales of goods is an endogenous process where the more successful the authentic producer is (in terms of sells/profit), the greater the likelihood counterfeiters will enter the market and try to copy the brand. As such, there is a positive correlation between the number of authentic products sold and the number of counterfeits on the market (i.e. the more successful is a brand, the more counterfeiting there is). It is not necessarily the case that counterfeiting causes increased demand for authentic products, although it can occur in that counterfeit and pirated products can inform consumers about the authentic good and increase demand for the authentic good (Shapiro and Varian, 1999; Conner and Rumelt, 1991).

An important element weaved into the key theoretical developments in this area is the problem of asymmetric information. Grossman and Shapiro (1988) describe it as two types of markets functioning side-by-side with different forms of asymmetry, one with "non-deceptive" counterfeit goods and one with "deceptive" counterfeit goods. According to Grossman and Shapiro (1988), non-deceptive counterfeiting refers to sales of fake goods to perfectly informed consumers aware they are purchasing a counterfeit because they can distinguish the fakes from the legitimate by where they buy the goods or by close inspection. "Deceptive" counterfeiting, on the other hand, refers to trade of fake goods with imperfectly informed consumers that may not be aware the good being purchased is a counterfeit. This can happen if the counterfeit is being sold through legitimate supply channels (i.e. a manufacturer distributes product through its retail outlet that has been infiltrated by counterfeit) or when the quality of the fake good is difficult or costly to assess at point of purchase.

While lots of studies have used variants of the basic model just described to evaluate firm behaviour within these markets (both the legitimate firm and the counterfeiter), the emphasis of the empirical work drawing on these theories has been on (a) impact on or response of authentic firm (Qian, 2011; Varian, 2005), (b) the price of authentic goods and counterfeit goods (Qian and Xie, 2011), and (c) the effectiveness of enforcement at deterring counterfeiting (Qian, 2008). We are not aware of any studies that attempt to structurally estimate the size of the counterfeit market using information about authentic firm sales.

Studies on the Behaviour of Consumers and Social Welfare. The second broad area of literature pertaining to counterfeiting has to do with consumers' behaviour and social welfare. A number of marketing studies have considered the determinants of consumers' willingness to buy counterfeit products in the context of non-deceptive goods. Studies based in the United Kingdom unveil the relative importance of different factors. Bian and Moutinho (2009) use focus groups and interviews to show that the construct of "brand personality" is the most powerful predictor of the consideration of the counterfeit product. Swami et al. (2009) highlight the role of attitudes towards counterfeiting and age (older consumers tend to show lower willingness to buy counterfeits) in their structural equation models, comparably to the hierarchical regression models in the study of Furnham and Valgeirsson (2007). Studies based in developing countries show similar patterns. Cheng et al. (2011) also employ structural equation modelling to Vietnam data and come to similar conclusions about the importance of subjective norms for willingness to buy counterfeits, together with perceived affordability. Data on Slovenian consumers is analysed in the work of Koklic (2011), confirming the importance of what he calls "moral intensity" and risk perceptions. Furthermore, different types of goods rely on specific taste patterns in the demand for counterfeits. For example, the willingness to buy counterfeits of luxury goods typically stems from social motives, as found by Wilcox et al. (2009).

Another way of gaining insights into the unobserved nature of the demand for counterfeit goods is through revealed preferences, as opposed to the preferences that can be reported in consumer interviews or surveys. An experiment was run by Harvey and Walls (2003) in which subjects were assigned real money to make a decision between an original and a fake good under varying scenarios of prices, probability of detection and penalty. They find that equivalent increases in the price of the authentic good and the expected penalty (probability of detection x penalty) induce consumers to substitute away from the counterfeit, and also that there are significant differences in the propensity to buy counterfeits across the two experimental locations (Las Vegas and Hong Kong).

Several studies have evaluated the impact of counterfeits entering the market on consumer welfare or social welfare (Yao, 2005; Scandizzo, 2001; Higgins and Rubin, 1986), but most have been theoretical in nature. In general counterfeiting is believed to reduce consumer welfare from the stand point that it leads to a higher price of the authentic good, in an effort to differentiate itself from the counterfeits (Qian, 2008; Yao, 2005). Scandizzo (2001), however, provides a particularly interesting theoretical model that considers the importance of a country's income distribution when assessing the effects of counterfeiting. A key insight from his theory is that consumer welfare will actual rise in the presence of cheaper imitations when the typical income within a country is low. This is because the presence of imitations/counterfeits makes otherwise unobtainable goods available to the general population, who might not care so much about quality. Of course, in the case of pharmaceutical products and other public health/safety goods, poorer quality imitation goods that are substandard or fake certainly hurt consumer welfare even in poor countries (Khan and Ghilzai, 2007).

Studies Attempting to Measure the Size of the Counterfeit Market. While the importance of counterfeiting has been recognized by the private and public sectors for quite some time, the intrinsic difficulty in building a practical and empirical understanding of the phenomenon is reflected in the relative scarcity of estimates of its magnitude in the literature, particularly the academic literature.

A number of studies exist in the non-academic realm that try to quantify the magnitude of counterfeiting across a broad variety of products. The general structure of the estimation process is built off of information on the number of infringements, the substitution rate (i.e. the number of legitimate goods that would have been bought in absence of the counterfeit), and the price at which such units would have been sold. The product of these three factors represents the value of sales lost by the IPR holder and is typically used as a measure of the value of counterfeiting. Each of these factors poses key challenges for measurement, due to the illicit and thus unrecorded nature of the phenomenon and the difficulty of getting at a meaningful substitution rate and counterfactual price, as testified by the richness and complexity of demand drivers and feedback effects (on equilibrium quantities and prices) documented in the academic literature. The majority of existing estimates thus stem from one-time sector-specific efforts that often lack transparency and are forced to make simplifying, sometimes implicit, assumptions. Examples of studies following this type of structure include studies by the Center for Economics and Business Research (2000) and Allen Consulting (2003). They rely on incidence factors of counterfeiting provided by industry associations or other studies to compute the size of infringement, and on consumer surveys to compute substitution rates.

The first study attempting to get at the global counterfeit market across sectors, including only internationally trade goods, was an estimate by OECD (2008) of $250 billion in 2005. Frontier Economics (2011) built off of this analysis by using the OECD method for internationally traded goods and including domestically produced and consumed counterfeit and pirated products and digitally pirated products. The OECD method is "data driven" in that the volume and value of counterfeiting and piracy is based on the amount of illicit trade (proxied by number of seizures) and legitimate trade between countries using estimates of value added by industry. A major criticism of this method is that it is based on law enforcement data, particularly seizures of counterfeit goods. The difficulty with using seizure figures to understand the scale of counterfeiting is that there are a variety of factors completely unrelated to the number of counterfeit goods that influence seizure numbers. For example, the counterfeit articles must be detected and identified as counterfeit by customs officials and therefore the number of counterfeits will increase if, for example, the skills of customs agents improve, technology to identify counterfeit goods improves and/or companies provide more intelligence to customs agents.

One alternative to the flawed estimation strategies just described relies on so called "mystery shopping", which consists of purchases of the same specific products from a random sampling of outlets that are then sent to experts for examination to determine if the goods are authentic or counterfeit. An example of a recent study using this approach comes from the European Alliance for Access to Safe Medicines (2008), which found from their mystery shopping study that 62% of medicines in their sample are substandard or counterfeit. The power of this technique is that it is possible to identify counterfeit goods even when the consumer is unable to distinguish the actual authenticity. The challenge of this approach, of course, consists in developing a robust sampling design in a cost-effective manner such that broad inferences can be drawn about the various targeted products on the whole population. Doing so can be extremely expensive and cost-prohibitive if done on a regular basis.

It is the lack of an empirically satisfying methodology that drives the efforts behind the current paper. We look to apply an economic model structurally derived from theory to generate a method for estimating the size of counterfeit markets that can be generally applied to a large range of counterfeited products. The key advantage of estimates based on our economic model is that it can incorporate a variety of simultaneously considered factors (unknown quality, price, replacement ratio) to project anticipated sizes of the market for either different goods or a country as a whole. Further, it can be easily (and at relatively low cost) modified to consider alternative factors not yet incorporated. The disadvantage is that the model is only as good as the logic and data that underlies it. It therefore suffers from whatever omitted variable biases might exist for factors not considered or those that are poorly measured. Thus, to help us assess the extent to which the logic of this model holds, we apply the model to estimate the level of counterfeit for a single technology product with data from a single firm and compare estimates from our model to those generating by the firm using their "gold-standard" shadow-shopping methodology.

III. Theoretical framework

The theoretical framework we adopt builds off Singh and Vives (1984) in which an economy contains a monopolistic or oligopolistic sector competing on quantity, depending on the substitutability of competitors' goods. We add to this theory a mechanism for counterfeiters to enter and obtain a share of authentic producer's submarket, incorporating aspects of the model by Grossman and Shapiro (1988). We now summarize the key features and insights of the model.

Beginning with the supply-side and nature of firm competition, Singh and Vives (1984) describe a market in which there is varying degrees of substitution between goods and of heterogeneity in the products themselves (e.g. product differentiation). For firms producing closely substitutable although differentiated goods, the model implies an oligopoly market. In this setting, firms choose a quantity contract and are committed to supply a predetermined quantity, independent of the action of a competitor. Singh and Vives (1984) present a two-stage option where firms first simultaneously commit themselves to a type of contract, either price or quantity, and afterwards compete on the type of contract selected.

On the demand-side, a representative consumer purchases products by maximizing utility subject to a budget constraint. Given quantities selected by firms, prices are determined through consumer demand; although oligopolistic firms have some control over pricing. Demand is downward sloping in its own price and increases with increases in the price of the competitor's good (if the goods are substitutes). When goods are substitutes rather than complements and demand is linear, quantity competition is a dominant strategy equilibrium and thus Pareto superior from firms' point of view (Singh and Vives 1984). This supports the idea that firms in monopolistic and oligopoly markets initiate supply decisions by setting quantity. In these markets, firms consider the total demand curve and commit to supply a predetermined quantity as a share of total demand.

At the margin, a change in production observed by an authentic firm in an oligopoly or market leader in a monopolistic market would generate a measureable change in total supply in the market since by definition they maintain a sizeable share of the total market. Because of this, these firms act as if they face some known share of total demand and set quantity accordingly. Conditional upon assumptions of its competitors' behaviours[2], a firm selects quantity and hence determines price in the market at a level that maximises its profit given the known market demand and market share.

As described earlier, authentic firms compete to sell quantity in a second stage. During this stage, we allow counterfeiters to enter a firm's submarket (e.g. share of total demand). Grossman and Shapiro (1988) show counterfeiters enter when an authentic firm credibly offers surplus in excess of that offered by other brands and/or consumers are imperfectly informed about products. Consumers then expect counterfeits may account for some fraction of a labelled product. Grossman and Shapiro

[2] This differs from a market of monopolistic firms in which production changes do not alter price and quantity of its competitors.

(1988) describe how consumers form such expectations, which influences their brand choice. When counterfeits enter a market, the share of counterfeits is determined by an authentic firm's decisions regarding price, quality and output.

An authentic firm utilizes information, such as market share, in predetermining, or setting expectations, of quantity and makes purchasing and supply-chain decisions accordingly. At the margin, the authentic firm can drive counterfeiters out of its submarket by changing its price-quality vector slightly in an appropriate direction; however, it would not do so if such a deviation was not profitable (Grossman and Shapiro 1988). As such, firms may maximise profit with counterfeiting levels above zero. Its decisions influence whether and how much of its demand it shares with counterfeiters. The extent to which firms achieve expected sales depends on a number of multi-level factors, including product, firm and market, which may result in expected quantities deviating from actual quantities in the short-run.[3] Furthermore, counterfeiting may be one potential factor contributing to a deviation between annual forecasted and actual quantity (Goel and Nelson 2009).

With this general framework, we can describe an empirical specification that links counterfeiting to increased deviations between expected and actual quantities supplied.

IV. Empirical strategy

Relying on the assumption that counterfeiters are only interested in entering markets for which there are some sort of rents, we can adopt the following two-stage empirical strategy to identify the amount of unexplained forecasting error that is caused by counterfeits and aggregate that up across markets to get the total impact. We consider for now the case of non-competitive markets, specifically an oligopoly, where a firm is able to set its own price.[4] Based on this price, it determines the quantity supplied to the market, meeting either the entire market demand for its product or its anticipated share based on that price. Thus, variation in price/quantity, in the absence of counterfeits, would only occur because of one of the following occurring: (1) Firm factors shifting the cost of production unexpectedly and hence profit-maximising output; (2) Demand-side factors shifting the

[3] We assume the long-run difference between expected and actual quantities is zero.

[4] The model can be similarly applied to a monopolist or discriminating monopolist producing a differentiable good.

market demand (e.g. change in disposable income, new product substitutes (or complements) enter (leave) the market, etc); or (3) Market factors altering the structure of supply or demand (e.g. natural disaster affecting supply-chain; government regulation change). If these factors are held constant and the quantity of product a firm is able to sell (at its selected price) is below expected, this is an indication that a counterfeiting product has entered the market and taken away some of the market demand. In other words, the amount of counterfeit product can be 'backed out" by considering how much the oligopoly or monopolistic competitive firms expected to sell and how much they actually sold.

More formally, consider the oligopoly firm selects a price (*p*) and, hence, the quantity (*q(p)*) it will produce conditional upon setting that price. The firm is not yet sure it can sell its entire quantity for that price; it is a prediction or forecast of quantity it expects to sell ($q^e(p)$). It may over- or under-estimate how much it can sell at that price and it will actually sell another amount, $q^a(p)$. Therefore, the firm will have some amount of a forecast error, $q^*(p)$, which is the difference between the amount expected to sell and the amount actually sold, or $q^*(p) = q^e(p) - q^a(p)$.

As described above, there are a number of factors completely unrelated to counterfeiting that might vary unexpectedly from the firms' forecast leading the firm to sell a different number of units than expected. It is presumed that the firm develops expectations about the product, market and demand factors that will influence its forecasts, but the firm is not always correct about how all relevant factors will move. For example, there may be an unexpected amount spent on marketing of the product because of a marketing campaign going better/worse than expected (product-specific). Similarly, the firm might unexpectedly gain entry into a new market that it had previously not anticipated to enter for another six months (firm-specific). Alternatively, there may be a financial crisis in a given market that impacts consumers' willingness to buy consumer goods (market-specific). Each of these can contribute to a different quantity sold than originally expected, but we would label those as "explained" factors that could be easily identified post-hoc. Nonetheless, they lead to a legitimate over- or under-estimate of quantity sold that is different than that caused by unobservable factors (like counterfeiting) and we want to take these post-hoc known factors out of the estimate.

In the first stage then, we calculate the proportion of the forecast error that can be explained by these ex-post unanticipated market or industry specific factors. More formally, we expect that each firm can estimate some form of the following equation:

$$q^*_{ijkt} = \beta_1 x_{ijt} + \beta_2 y_{ijt} + \beta_3 z_{jkt} + \varepsilon_{ijkt}\,, \qquad (1)$$

where q^*_{ijkt} is the total forecast error at time t for firm i in a market (which we define as by product j and country k); x is a matrix of product-specific variables that were not anticipated so not included in the original forecast of $q^e(p)$; y is a matrix of firm-specific variables that reflect unexpected changes in relevant firm factors, and z is a matrix of market and demand-level variables that might contribute to a forecast being off (and is therefore product-country specific (jk), not firm specific).

The regression specified in equation (1), therefore, includes as regressors only those things that the firm did not accurately know when developing its original forecast for the period but learned post-hoc. The coefficients $\beta_1, \beta_2, \beta_3$ tell us the relative importance of these factors, firm and market shocks, respectively, in predicting the error. The term ε_{ijkt} represents unobservable factors that also influence the forecasting error, which might include random noise but would also include unobserved fluctuations in the amount of counterfeiting going on in the particular product market.

By estimating equation (1) empirically, each firm can generate an estimate of the predicted residuals ($\hat{\varepsilon}^*_{ijkt}$) which partials out the explained variation in the forecasting errors (caused by unpredictable changes in *x, y* or *z*). It is this unexplained variation in the forecasting error, represented by the predicted residuals ($\hat{\varepsilon}^*_{ijkt}$) that is then used in our second stage model. It is used to understand what fraction of the unexplained variation in authentic product sales is accounted for by counterfeiting.

Of course, the key to being able to use this market logic to estimate the size of the counterfeit market depends on having good information in which to base expected sales holding actual market conditions constant (or, more accurately econometrically accounting for them). The current assumption that firms will have this information is based on an understanding that they need to be able to have an appropriate amount of inventory available and plan resources (e.g. labour costs, interest payments, etc). For this reason, firms make forecasts about how much quantity they expect to sell. In practice, this may be done through a variety of approaches including simple approaches of considering past trends in sales and sales of similar products to more sophisticated econometric techniques accounting for a variety of factors. [5]

The second stage of the empirical process is to assess what proportion of the remaining forecasting error can be attributable to counterfeiting. In a second regression, we estimate the relationship between the "unexplained forecast error", $\hat{\varepsilon}^*_{ijkt}$, for firm i operating in product market jk at time t and factors of counterfeiting in those same markets. Formally, the second stage regression is of the following form:

$$\hat{\varepsilon}^*_{ijkt} = \beta c_{jkt} + u_{ijkt}, \qquad (2)$$

where $\hat{\varepsilon}^*_{ijkt}$ is the amount estimated previously for the unpredicted forecast error of a product by firm i at time t and c is a matrix of variables related to counterfeiting that contribute to the unpredicted error in forecasting (discussed in greater length below). Firms may over- or under-sell the amount forecasted because of reasons completely unrelated to counterfeiting and for market factors not yet taken into consideration by the model[6]; this is captured by the new error term u_{ijkt}.

[5] We recognize that not all firms may be able to estimate a formal model to generate their unexplained forecasting error measure, which will lead to an overstatement of the unexplained forecasting error in the second equation. Assuming that variation in counterfeiting is not systematically linked to unexpected changes in firm, factor, or market characteristics, the use of a grosser measure of unpredicted forecasting error would just add noise to our second stage of the model.

[6] In practice, this can mean demand out-stripping supply and firms need to make additional purchase orders to the normal purchase schedule.

Upon estimation of equation (2), one can generate a prediction of the conditional mean ($\hat{\beta}c_{jkt}$), which is a direct estimate of the amount of unexplained forecasting error that can be predicted by counterfeiting supply and demand factors:

$$\hat{\beta}c_{jkt} = \text{Amount of counterfeiting} \qquad (3)$$

V. Data

To test the validity of the proposed method, we obtained confidential data from an industry partner whose specific technology has been the target of counterfeiting in various places across the globe. The data come from a single firm that is the internationally leader in the sale of this specific technology offered through a variety of products patented by the firm in numerous countries. Due to the persistent threat of counterfeit producers, the firm independently engages in estimation of counterfeiting activities using an industry gold-standard, which involves conducting shadow shopping in selected markets on an infrequent basis. Estimates from these selected markets are then extrapolated to sales in all markets and other countries in which the firm operates. Given the tremendous cost of collecting data using the shadow shopping method and the uncertainty of how to extrapolate properly to other markets, the firm was willing to share with us proprietary data on forecasts and actual units sold in 30 different countries for over 50 different products sold during the period 2006-2011 so we could test our model and compare it to their estimates. Further, for a subset of the data, the firm provided to us information on market factors they use to understand deviations from forecasts and in the construction of new forecasts, including sales by competitors.

Not all of the products for which we were provided information on forecasts and actual units sold contained the firm specific product and market information for the years of interest. Thus, the final data set used for testing our model contained information on 45 related products sold in 16 countries over the period 2006-2011, resulting in a total sample size of 3,300 observations. Descriptive statistics on the main variables used in our analysis, slightly camouflaged to protect the identity of the firm, are provided in Table 1. As can be seen by the mean values and their very large standard deviations for forecasts and actuals, there is considerable variability in the number of units sold for each product across markets, with some markets selling relatively small amounts of the product and other markets being quite substantial. In general and on average, forecasts are larger than units sold, as is indicated by the positive mean value for the difference in forecasts and actuals (median value is also greater than zero). The sales by competitors could affect their own market sales, and if pure volume is a good indication, it appears that at least two of the competitor product types are large enough to create some serious competition in select markets. The base technology previously sold in a given market is used by the firm to help formulate future forecasts, which is why we also include it in our first stage analysis.

We added to these firm-specific data information from a variety of sources that help us capture general correlates of market demand within each country. First, we include a measure of the rate of growth of Gross Domestic Product (GDP) to capture changes in income within the country. As this is a variable that is frequently used to project forecasts by the firms, we include this measure in our first stage regression, not the latter. To capture general market demand in the second stage, we include a second measure correlated with demand, international tourism. Both measures were obtained from the World Bank Development Indicators.[7]

Measures of the susceptibility of these products to IPR infringement, which are used in the second stage, are obtained from World Bank Surveys, which collects national-level data on a series of topics systematically from countries across the globe, including economic prosperity; trust in the legal system; and so on. For our study, we draw on three indices constructed by the World Bank from data collected within these surveys, namely indicators of the rule of law, control of corruption, and government effectiveness. Ex-ante we expect that the rule of law and control of corruption variables are more likely to related to counterfeiting than the government effectiveness variable, but in this pilot exercise of the theory we experiment with all three variables.

The World Bank's rule of law index is constructed from a series of variables capturing respondents' perceptions about how well the rules of society are abided to. Variables used in the construction of this index include beliefs regarding the effectiveness of the police, confidence in the

[7] http://databank.worldbank.org as of March 20, 2012.

policy system, whether intellectual property protection is weak, speediness of the judicial system, enforceability of contracts and trust in the functioning of the criminal justice system. The control of corruption variable, as defined by the World Bank, captures peoples' perceptions regarding the extent to which public power is used for private gain. Questions used in the creation of this index include the frequency with which firms are required to make payments in a variety of settings (favourable judicial decisions, public utilities, etc.), the frequency of corruption amongst public institutions such as the state legislatures and customs and the existence of country anti-corruption policies. The government effectiveness measure attempts to assess how respondents feel about the quality of their public services, civil services, policy formation, and independence from political pressure.[8]

We also consider as additional variables in our second stage analysis two indicators of the complexity of customs procedures, namely the number of documents required to import goods (documents) and stringency of a country's customs procedures (custom's burden). In the final results presented here, we only use the measure of custom's burden, as we found that the documents measure is highly correlated with too many of the other variables included in the model.

VI. Results

Table 2 shows the results from our estimation of the first stage regression, where we attempt to explain post-hoc why actual units sold deviate from firm forecasts (i.e. identify the amount of "explained" forecasting error). While the actual sources of information used to predict deviations in forecasting errors are relatively limited, the small set of controls predicts nearly a quarter (22%) of the variation in the forecast errors. We find that proportion of products sold with a particular characteristic tend to lead to larger forecasting errors, which is consistent with findings from Qian (2011) that the volume of authentic goods sold is positively correlated with the volume of counterfeits sold given this characteristic of common of the products most frequently counterfeited.

The results also show that the firm does a better job forecasting in markets where there is more of the base technology making use of their products, as higher base technology units is

[8] The full set of questions related to the construction of each of these indices can be found at info.worldbank.org/governance/wgi/pdf/rl.pdf.

associated with lower forecast error. We interpret this result as suggesting that there is greater predictability in markets with a larger, more stable technology base, so there is less uncertainty about market growth and the like. Unexpected increases in the sales of competitor goods, however, reduces the number of units sold by this firm and leads to larger forecasting errors, which is consistent with expectations. Interestingly, the model also suggests a positive monotonic increasing effect of year, suggesting that the firm is getting worse at achieving forecasted sales units over the time period examined. This is not too terribly surprising, however, in light of the global recession that occurred in the latter part of the period being evaluated.

Product fixed effects, which are also included in this first stage regression but suppressed from the table, were highly statistically significant as a group and for particular products. This suggests to us that there is important variation across products in the firm's ability to reliably predict forecast sales, which may have something to do with the product (if it is a new product or quickly growing one) or something to do with the markets in which the product is being sold. Not all the products are sold uniformly in each of the 16 countries.

Regression errors from this first stage regression, which represent the "unexplained forecasting error" are retained and used then as a dependent variable in a second stage regression. In this second stage, we now examine how important counterfeiting measures are in explaining the remaining unexplained forecasting error. Results from four alternative specifications of this second stage regression are shown in Table 3. These alternative specifications are run so that we can show the relative importance of specific counterfeit measures independently, as the variables are highly collinear which makes it difficult to interpret their results in the final specification when all of them are included together.

We see in looking across Columns I, II and III that the unexplained forecasting errors are lower in countries with a stronger rule of law, stronger control of corruption, and higher levels of government effectiveness. Individually each of these measures come in strong and statistically significant in the manner we would expect, suggesting that countries that are tough in enforcing penalties and sanctions on violators of IPR agreements and/or who are tough on crime in general, with a strong, effective government have lower levels of counterfeiting. However, when all three variables are included simultaneously into the model, the signs and significance on the rule of law and government effectiveness variables change. Government effectiveness remains negative but becomes statistically significant and the rule of law variable becomes positive and marginally significant (at the 10% level). In light of the other factors held constant in the regression, most specifically the direct control for corruption, it appears that countries with a stronger rule of law might be associated with greater counterfeiting. Control for corruption, however, remains strongly negatively associated with unexpected forecast errors, getting even larger in magnitude with the other variables included simultaneously.

Unexplained forecasting error is larger in countries with a higher customs burden, and statistically significantly so when measures for the control for corruption are included. To the extent that a larger unexplained forecasting error represents higher levels of counterfeiting, this would indicate that counterfeiting is a bigger problem in countries with a higher customs burden. Whether it is the policy that drives this association or that countries with significant problems are more likely to adopt more burdensome custom practices cannot be said. But the model clearly identifies a positive association between the two.

Our measure for international tourism, which proxies a higher level of general market demand, is positively associated with unexplained forecasting errors in each of these models. If international tourists were coming into the country and buying authentic products, then one would expect the association to be negative. The fact that it is positive suggests that the international tourists may be helping support counterfeit markets. This might be true for two reasons: (1) tourists might be easier targets for counterfeiters to deceive (because they are less familiar with the market, legal framework, etc. and also only one-time shoppers); and (2) local authorities might be more lenient towards counterfeit markets in tourist locations as a sort of “marketing lever”. We cannot assess if either of these are true in our model, but simply offer them as a possible explanation for the finding.

Also included in the second stage model are year, product and country fixed effects. Interestingly, the year effects do a better job picking up the global recession effects when all three of our strength of government variables are included, possibly because these three indicators combined do a better job of separating out Europe and the US from India, China and other developing countries.

As the goal of this exercise is to use the second stage model to predict the level of counterfeiting in each of our national markets, we use the regression coefficients from the model presented in Column IV to derive estimates of the amount of counterfeiting in each market because it is the model with the highest R-squared. Importantly, none of these models have very large explanatory power in the second stage, but that is not too surprising given that there remain a variety of other factors that influence errors in forecasts besides counterfeiting. Thus the real test of the model will be assessing how well its predictions correspond to estimates from the firm for each of the markets.

Table 4 provides summary statistics of the predicted level of counterfeits (aggregated to the country, product level) as generated by the model and those reported by the firm using their shadow-shopping method with extrapolation. It appears in looking at these numbers that the RAND model estimate is generally lower than the firm's estimate both in total units and as a percent of actual units sold. This is true in total and across all years. As we do not have available to us the error bands for the firm estimates, we can only assess the extent to which the firm estimate falls within our 95% confidence intervals derived from our model. We do this on a product-by-product and year-by-year basis and find, as reported at the bottom of Table 4, that 40% of the time the model generates estimates that are not statistically differentiable from the firm estimate. The degree of overlap between the model estimate and the firm estimate will in fact be greater than this given the firm's estimates are themselves extrapolations (and hence have confidence intervals). Without a measure of their modelling error, however, we cannot say how much overlap there would be, so the 40% should be viewed as a lower bound.

It is not terribly surprising that the RAND model predicts lower levels of counterfeits than the firm's gold standard, particularly in light of the very general information that is being used to build the estimate. One would expect that the precision of the model will be reduced as you move beyond information that is specific to the firm or industry; similarly, it is likely that the model could be improved if more industry or sector-specific information were included. The advantage of relying on broad information is that it allows the same approach to be applied across a variety of goods and sectors, and demonstrates that even this broad approach generates estimates that are indeed plausible and meaningful. But there is a trade-off of using this broad approach; it comes at a cost of lower precision and, in the case of this one particular product group, a downward bias.

Another very important aspect to consider when evaluating the model is its ability to replicate trends in the amount of counterfeiting over time. As can be seen in Table 4, the share of counterfeit as a percent of actual units sold generated from the RAND model follows the same general downward trend between 2006-2010 as the firm model does, and also captures the uptick in 2011. This is shown visually in Figure 1. However, the RAND model does not do a very good job capturing the firm's estimated rise in counterfeiting in 2007. Unfortunately, we did not collect data from the firm regarding when their estimates of counterfeiting were data based versus projections from a model, so we cannot be certain at this point if this deviation is due to our model or perhaps a forecasted error on the firm's behalf (due to the immediate return to a decline in 2008). Additional investigation is warranted to identify whether the firm had confidence in the unexpected increase their data report for 2007.

While the level of counterfeiting estimated by the two stage model is clearly biased downward in terms of the level estimated, the model appears to do a very good job capturing broad trends in counterfeiting over the time period examined. If the ability to mimic trends is observed over a longer period of time and/or for other firms, then it is this trait of the model that will likely be the most useful to policymakers. While understanding the total level of counterfeiting may be valuable to particular firms, policymakers care more deeply as to whether particular strategies or policies are improving the situation or making it worse. A model that can accurately identify changes in the trend of counterfeiting would be very useful for this purpose.

VI. Conclusions

The development of new methods for estimating the size of the counterfeit goods market is an important activity in light of the significant limitations of existing methods (OECD, 2008) and the desperate need of policy makers to identify and assess policies that are effective at reducing it (OECD, 2008). Firms and governments alike expend extensive resources in efforts to limit counterfeiting because in some cases the imitations may be dangerous or a risk to public safety, but little can be known with certainty regarding the effectiveness or cost-effectiveness of various measures without a reliable method for measuring the extent of the problem in the first place.

In this paper we propose and pilot a new methodology grounded in economic theory that shows promise in terms of assessing trends in the size of the counterfeit market. Though encouraging, the pilot study has important limitations that need to be considered when interpreting the results. First, we are only able to test the model with data from a single firm operating in just one sector of the economy. It will be important to identify through future work whether the basic model performs reasonably well for other industries and sectors, and if not, identify what aspects of those industries/sectors make it less useful. It may be that the specific macro-level measures of IPR susceptibility vary significantly across different sectors (for example, broadband access and number of internet users may be more relevant for pirated goods than physical goods). Future work should consider the utility of considering sector-specific models that enable the incorporation of a broader set of macro measures. Such a modification does not reduce the utility of the general approach here; in fact, to the extent that more specific measures are required in different sectors, estimation by sector could lead to improved precision of counterfeit estimates from the model, which can then be aggregated post estimation to understand overall trends across multiple products groups and market sectors.

A second limitation of the model is that it cannot capture the presence or amount of counterfeit goods that do not directly compete with authentic goods (i.e. where the substitution rate between authentic good and counterfeit good is very low or equal to 0). To the extent that this represents a relatively large share of the total counterfeit good market, this could be a big problem and lead to an even larger underestimation of the market. The products being evaluated here, because of their direct tie to a base technology purchased separately, are all goods where counterfeiters would actually be substituting for the authentic good (though perhaps not as high as 100%). Thus, consideration of the model's performance when considering a counterfeit market that does not directly compete with the authentic good will be important in future efforts.

Even with these limitations, this paper makes an important contribution by developing, implementing and testing a promising new approach for estimating the size of the counterfeit market, which can be used to assess the impact of counterfeiting within particular industries, sectors of the economy, or for an economy as a whole. When estimates from our model are tested against an industry gold standard, estimates derived from shadow shopping, our model performs reasonably well in that model estimates are consistent with those of the gold standard in 40% of the cases. Interestingly, we find that the matching is better in some years than it is in others, raising an interesting question regarding what might be driving this and whether it is a function of the model or other market forces.

Should future tests of the model prove similarly promising, a new relatively low-cost strategy for understanding trends in the amount of counterfeiting in different markets may emerge, providing a more methodologically rigorous approach then prior methods that rely on seizure information. However, the model should be further tested in other industries and for a range of products before such a conclusion can be drawn definitively.

Importantly, the proposed new methodology generates results consistent with prior work showing that the level of counterfeiting is inversely related to the strength of the governments' efforts to deter it as well as the degree of corruption within the system. This was true even after controlling for country fixed effects in a relatively short panel of data, suggesting that applications of the model on more data (either in terms of years or countries) may generate even more promising results than those presented here. A key implication of our model is that broad national policies can be effective at influencing the level of counterfeiting within the market as well as trends.

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Figure 1: Trends in the Level of Counterfeiting as Indicated by the Firm's "Gold Standard" and the RAND Model

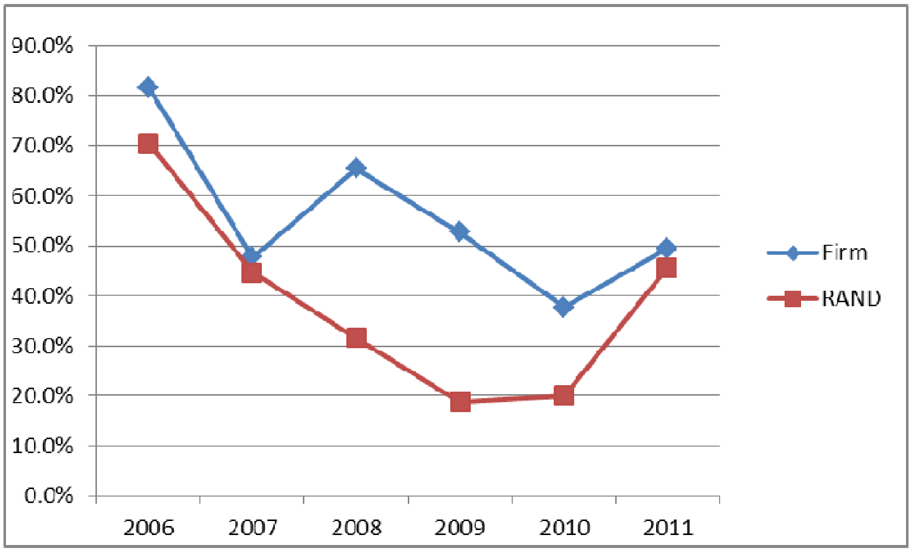

Table 1: Descriptive Statistics on Key Firm and Counterfeiting Measures

Dependent Variables		
	Mean	**Std. Dev**
Firm Forecasts (Units Sold)	708,957	1,941,571
Firm Actuals (Units Sold)	695,984	1,977,649
Diff: Forecasts - Actuals	11,798	220,558
Independent Variables -First Stage		
	Mean	**Std. Dev**
GDP Annual Growth	2.9	3.89
Existing Base Technology Previously Sold	953,416	1,875,790
Competitor Sales Product Type A	187,244	421,244
Compeitor Sales Product Type B	96,629	171,786
Competitor Sales Product Type C	24,356	36,685
Independent Variables - 2nd Stage		
	Mean	**Std. Dev**
Rule of Law	0.89	0.8
Control of Corruption	0.94	0.9
Government Effectiveness	0.97	0.67
Custom's Burden	4.46	0.54
International Tourism	7.46	3.92
N	3000	

Notes: Product data is from countries within North America, Europe, Central, South, and East Asia; spans the 2005-2011 time periods. Data captures 45 unique products across the 2005-2011 time period.

Table 2: Results from First Stage Regression of Product Specific Forecasting Error

1st Stage Dependent Variable		
	Forecast Error (in 1,000 units)	
GDP Growth	1.241	
	(1.801)	
% Sold with Product Characteristic X	106	***
	(28.219)	
Install of Base Technology	-4.08E-05	***
	0.000	
Competitor Sales Product Type A	0.0873	
	(0.06)	
Competitor Sales Product Type B	0.233	***
	(0.075)	
Competitor Sales Product Type C	0.468	*
	(0.253)	
Year	21.657	***
	(7.967)	
R-Squared	0.220	
Product Fixed Effects	Yes	
Cluster	Product	
N	3300	

Notes: Forecast Error, the dependent variable in the first stage is defined as the (Forecast-Actuals). Product data is from countries within North America, Europe, Central, South, and East Asia regions; spans the 2006-2011 time periods. Ordinary Least Squares regressions include product fixed effects and standard errors are clustered at the level identified at the bottom of the table. Statistical significance is indicated as follows: *** Denotes significance a the .1% level; ** denoted significance at the 1% level; * denotes significance at the 5% level.

Table 3: Results from Second Stage Regression of Unexplained Forecasting Error

	Dependent Variable: Residuals From First Stage Regression							
	I.		II.		III.		IV.	
Rule of Law	-97.74	***	---		---		230.89	
	(21.05)		---		---		(159.55)	
Control of Corruption	---		-121.48	**	---		-283.32	*
	---		(36.71)		---		(98.57)	
Government Effectiveness	---		---		-130.93	*	-32.41	
	---		---		(48.51)		(117.54)	
Customs Burden	97.08		96.14	**	92.44		53.07	**
	(47.59)		(44.56)		(51.50)		16.23	
Intern'l Tourism	12.49	*	15.97	**	13.27	*	13.86	**
	(5.48)		(6.31)		(6.55)		4.10	
Year_2007	50.84		41.17		54.59		25.18	
	(58.99)		(51.77)		(59.18)		(39.51)	
Year_2008	60.32		46.17		59.88		15.11	
	(58.41)		(46.96)		(58.02)		(27.17)	
Year_2009	47.36		26.62		38.79		-11.93	
	(64.47)		(51.95)		(60.41)		26.03	
Year_2010	42.96		27.74		40.69		-7.63	
	(66.14)		56.55		(64.33)		34.10	
Year_2011	11.21		-26.37		-8.36		-65.77	***
	(48.81)		(33.18)		37.80		15.89	
Country FE	Yes		Yes		Yes		Yes	
Product FE	Yes		Yes		Yes		Yes	
Observations	3300		3300		3300		3300	
R-Squared	0.03		0.04		0.03		0.05	

Notes: Forecast Error, the dependent varibable in the first stage is defined as the (Forecast-Actuals). Product data is from countries within the North America, Europe, Central, South, and East Asia regions; spans the 2006-2011 time periods. Ordinary Least Squares regressions include product and country fixed effects. Standard errors are clustered at the product level. Statistical significance is indicated as follows: *** Denotes significance at the .1% level; ** denotes significance 1% level; * denotes significance at the 5% level.

Table 4: Mean Value of Predictions of the Number of Counterfeited Goods and Comparison with Firm's Estimates

	Mean	Std Dev	Year 2006	Year 2007	Year 2008	Year 2009	Year 2010	Year 2011
Firm Estimate of Counterfeit by Product (In Units)	707,124.00	1,028,840	1,082,135	1,032,073	939,672	810,159	747,979	118,853
RAND Estimate of Counterfeit by Product (In Units)	383,539.00	357,855	311,877	711,685	515,178	505,091	186,527	279,937
Percent of Firm Estimates inside RAND 95% CI	39.6%		50.6%	21.5%	1.9%	59.2%	54.1%	15.9%
Firm Estimate as a Percent of Actual Units Sold	55.8%		81.6%	47.7%	65.4%	52.7%	37.7%	49.5%
RAND Estimate as a Percent of Actual Units Sold	38.6%		70.4%	44.7%	31.6%	18.9%	20.0%	45.6%