

A welfare analysis of spectrum allocation policies

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Economic analysis of spectrum policy focuses on government revenues derived via competitive bidding for licenses. Auctions generating high bids are identified as “successful” and those with lower receipts as “fiascos.” Yet spectrum policies that create rents impose social costs. Most obviously, rules favoring monopoly predictably increase license values but reduce welfare. This article attempts to shift analytical focus to efficiency in output markets. In performance metrics derived by comparing 28 mobile telephone markets, countries allocating greater bandwidth to licensed operators and achieving more competitive market structures are estimated to realize efficiencies that generally dominate those associated with license sales. Policies intended to increase auction receipts (e.g., reserve prices and subsidies for weak bidders) should be evaluated in this light.

1. Introduction

■ Competitive bidding to assign wireless licenses constitutes a substantial policy advance. Following their suggestion by Leo Herzel (1951) and Ronald Coase (1959), auctions were finally adopted by New Zealand in 1989 (Crandall, 1998), India in 1991 (Jain, 2001), and the United States in 1993 (McMillan, 1994). At least 25 other countries have instituted license auctions in recent years (Hazlett, 2008b).

The argument for using the “price system” to allocate wireless licenses is premised on three types of economic efficiencies:

- (i) elimination of rent dissipation associated with “comparative hearings” or “beauty contest” awards (Kwerel and Felker, 1985);
- (ii) assignment of licenses to the most productive suppliers, saving the costs of secondary market reassignments (Cramton, 2002);

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(iii) generation of public revenues, displacing taxes; the consensus estimate is that \$0.33 in social cost is saved for every tax dollar saved (Cramton, 2001; Klemperer, 2002b).¹

A healthy literature on the implementation of wireless auctions has emerged.² Revenues raised by government auctions are seen both as indicators of auction design efficiency and as appropriated surplus that increases social welfare by offsetting activity-distorting taxes. Consequently, auction success is typically measured by license receipts.³

In evaluating alternative bidding mechanisms, Paul Klemperer has written: “What really matters in auction design are the same issues that any industry regulator would recognize as key concerns: discouraging collusive, entry-detering and predatory behavior. . . . By contrast, most of the extensive auction literature . . . is of second-order importance for *practical* auction design” (Klemperer, 2002b, emphasis in original).⁴

This approach, “just good undergraduate industrial organization” (Klemperer, 2002b), is unassailable. But an essential analytical conflict is left intact: auction rules that alter market structure or operator performance produce welfare effects, and these spillovers may not be systematically incorporated. For instance, arguments are often advanced to improve license auctions by imposing reserve prices,⁵ extending credits to “weak bidders,”⁶ or restricting the number of licenses (to increase scarcity value).⁷ In addition, the social discount rate is ignored in auction processes that delay productive use of frequencies for months or years.

The problem is put into perspective with some simple estimates of social value. Empirical research undertaken a decade ago found the annual consumer surplus associated with U.S. cellular telephone licenses (issued in the 1980s) at least 10 times as large as annual producers’ surplus (Hausman, 1997; Rosston, 2001). Today, U.S. wireless phone market data yield an annual consumer surplus estimate of at least \$150 billion.⁸ The total revenue obtained from selling all wireless licenses (not just for mobile telephony) is just \$53 billion.⁹ Given that the latter is a present value and the former an annual flow, these data suggest that the ratio (CS to PS) is much above an order of magnitude.

Policies undertaken to improve license revenues, then, focus on a small fraction of the economic value at stake. Rules that increase auction bids but risk collateral damage—say, by reducing operator efficiency or market competitiveness—generate potential costs not properly evaluated by reference to rent extraction alone. This is true even when revenues raised by license auctions do, *ceteris paribus*, increase welfare.

We offer an extension of the Klemperer critique. Economists should not only consider market structure effects within auctions but should incorporate consumer welfare effects from wireless output markets whenever alternative auction rules influence not only public rent extraction but retail prices.

We hasten to note that Paul Klemperer has correctly diagnosed the temptation to favor monopoly rent creation over competitive output markets. Klemperer (2002b)

¹ Cramton (2002) cites a range of 17–56 cents.

² See McMillan (1994); McAfee and McMillan (1996); Cramton (1995, 2002); Moreton and Spiller (1998); Grimm, Riedel, and Wolfstetter (2001); Wolfstetter (2001); Binmore and Klemperer (2002); van Damme (2002); Klemperer (2002a, 2002b).

³ It is customary to adjust receipts by bandwidth allocated licenses and the population of the franchise area, such that prices are quoted in terms of “\$ per MHz per pop.”

⁴ Support for this view is also supplied in Binmore and Klemperer (2002) and Klemperer (2002a).

⁵ See Cramton (2002); Krishna (2002); Klemperer (2002a).

⁶ See Ayres and Cramton (1996); Rothkopf, Harstad, and Fu (2003).

⁷ See Wolfstetter (2001); van Damme (2002); Rothkopf and Bazelon (2003).

⁸ This lower bound can be calculated from historical price-quantity pairs for wireless minutes of use (Hazlett, 2008a). Hausman (2002) and Entner and Lewin (2005) obtain similar estimates.

⁹ The Federal Communications Commission raised \$52.6 billion through (and counting) the 700 MHz license auction completed in March 2008. Chloe Albanesius, *FCC Spectrum Auction Ends, Successfully, PC Magazine* (March 18, 2008), <http://www.pcmag.com/article2/0,2817,2277146,00.asp>.

comments on a proposal by Italian regulators (not, in fact, implemented) to eliminate a 3G¹⁰ license (and the competitor it would empower) in order to raise auction revenues: “[T]he approach was fundamentally flawed . . . it is putting the cart before the horse to create an unnecessarily concentrated mobile-phone market to make an auction look good” (Klemperer, 2002b).¹¹

In contrast, however, Klemperer endorses the policy implemented in 3G license auctions held in Belgium and Greece in 2001. Both countries appear to have raised incremental revenue by imposing reserve prices. The result was that each country sold three wireless licenses, with a fourth unsold. Klemperer credits the authorities for producing receipts of about 45 Euros per person, a rent extraction generating some public financing efficiency. Excluded from the analysis, however, is the fact that each unsold license was allocated approximately 35 MHz of bandwidth,¹² and that this frequency space could have been productively employed by a fourth network (if a willing entrant had come forth at a license price of between 0 and 45 Euros per capita¹³) or divvied up among the three incumbent networks to expand capacity.¹⁴

After calibrating an empirical model measuring the relationship between frequencies allocated to cellular service and retail prices, we find that the welfare cost of withholding spectrum via reserve prices likely exceeded public gains from the revenues raised in either Belgium or Greece. This is one frequently encountered example of how policies prescribed for license assignments alter market structure. The problem arises when the auction analysis does not then incorporate attendant welfare effects. We offer a critique of analytical partitioning that is asymmetrically broached.

Our empirical analysis focuses on wireless telephone service in 28 countries, of which 19 employ auctions to assign licenses. After adjusting for cross-sectional differences in demand and supply, we find that larger quantities of spectrum, as well as more intense competitiveness (measured by the Herfindahl-Hirschman Index), are strongly associated with lower prices. We then use the coefficient estimates from our model to perform simulations quantifying retail market effects associated with various policy changes. In general, auction rules intended to increase license rent extraction by restricting spectrum access are not welfare enhancing. Restricting the use of spectrum inputs is a relatively expensive way to raise public funds.

This article is organized as follows. In Section 2, we describe our empirical model and report regression results. Section 3 uses these estimates to simulate welfare effects of policy choices made in the design of license auctions. Section 4 offers a conclusion.

2. The relationship between spectrum and retail prices

□ **A simple model.** Consider a market where N firms will be producing a homogeneous mobile telephone service, with output levels given by q_i , where i identifies the firm. We assume there is no initial incumbent. Aggregate output is given by $\sum_i q_i = Q$. The market price associated with this output is defined by the inverse demand function $p(Q)$.

¹⁰ “3G” refers to “third-generation” mobile telephone services, commonly thought to encompass digital voice and high-speed data. First-generation consisted of analog voice, second-generation of digital voice and narrowband data.

¹¹ Klemperer (2002b) also (correctly) pronounces the Turkish auction outcome a “fiasco.” In auctioning two competing licenses sequentially, regulators set the winning bid for the first license as the reservation price for the second. The obvious strategy obtained: the winner of the first auction bid so high that no bidder was willing to match the reservation price for the second.

¹² Sources: Greece: National Telecommunications and Post Commission, Press Release (July 13, 2001), http://www.eet.gr/eng_pages/telec/umts/Main.htm Belgium: BIPT, “Communication of the BIPT Concerning the Results of the Auction” (March 2, 2001), <http://www.umts.bipt.be/EN/PR%20English.pdf>.

¹³ We here exclude the possibility of a subsidy to an entrant.

¹⁴ Although firms’ bidding showed they had extremely low private values for additional spectrum in these auctions, there may be—as we argue below—substantial divergences between private and social spectrum value.

Firm i has a cost function assumed to adopt the form

$$C_i(q_i) = c(K_i, S_i)q_i. \tag{1}$$

This implies constant marginal cost given a particular level of capital, K_i , and the amount of spectrum, S_i , allocated to the license awarded firm i . When quantity decisions are made, capital and spectrum are fixed and the prices paid for these resources are sunk. In order to focus the analysis on spectrum allocation policies, we assume symmetric investments ($K_i = K$ for all i). Marginal cost is decreasing in capital and spectrum, and these two inputs are substitutes (engineering cost models indicate that for a given level of service, as the amount of spectrum [MHz] increases, capital cost per subscriber falls [Reed, 1992]).

In what follows we assume Cournot competition. We denote market share as $s_i = q_i/Q$, and price elasticity of demand as $\varepsilon(Q)$. The spectrum allotted to a given license can be written as $S_i = \phi_i S$, $0 < \phi_i \leq 1$, where S is the total amount of spectrum assigned to wireless services. In such a context it is easy to show that a mark-up equation is defined by¹⁵

$$p(Q) = \left[1 + \frac{HHI}{\varepsilon(Q)} \right]^{-1} \sum_{i=1}^N s_i c(K, \phi_i S). \tag{2}$$

We interpret the equilibrium mark-up equation (2) as one where the supply depends on the elasticity of demand $\varepsilon(Q)$, the level of investment (K), the amount of allocated spectrum (S), and the Herfindahl-Hirschman Index (HHI).

We assume demand for wireless telephony to be a function of the price of wireless service (p), income level (Y), and the price of alternative telephone services (F).¹⁶ In principle, we can posit a constant elasticity of demand function for wireless telephony such that

$$Q = \lambda Y^\delta F^\rho p^\epsilon. \tag{3}$$

□ **Empirical estimation.** The empirical implementation of our model is based on the estimation of a system formed by an empirical mark-up equation, motivated by the variables in equation (2), and an expanded log-log version of the demand function given by equation (3). Both include nonlinear terms. The benchmark system is given by:

Empirical mark-up equation:

$$\begin{aligned} \ln(RPM_{it}) = & \alpha_0 + \alpha_1 \ln(Q_{it}) + \alpha_2 [\ln(Q_{it})]^2 + \alpha_3 \ln(HHI_{it}) + \alpha_4 [\ln(HHI_{it})]^2 \\ & + \alpha_5 \ln(Spectrum_{it}) + \alpha_6 [\ln(Spectrum_{it})]^2 + \alpha_7 \ln(Density_{it}) + \alpha_8 [\ln(Density_{it})]^2 \\ & + \alpha_9 [\ln(Spectrum_{it}) * \ln(Density_{it})] + \alpha_{10} Auction_{it} + \alpha_{11} NotCPP_{it} + \eta_{it} \end{aligned} \tag{4}$$

Empirical demand equation:

$$\begin{aligned} \ln(Q_{it}) = & \beta_0 + \beta_1 \ln(RPM_{it}) + \beta_2 [\ln(RPM_{it})]^2 + \beta_3 \ln(GDPpc_{it}) + \beta_4 [\ln(GDPpc_{it})]^2 \\ & + \beta_5 \ln(Fixprice_{it}) + \beta_6 [\ln(Fixprice_{it})]^2 + \beta_7 NotCPP_{it} + \varepsilon_{it}, \end{aligned} \tag{5}$$

where i denotes the country and t the period, and \ln stands for natural logarithm. Variables are defined as follows:

- RPM* Revenue per minute in constant 2000 US\$ for mobile voice services.
- Q* Output, measured as total minutes of use per month (totmin) in millions.
- HHI* Herfindahl-Hirschman Index in the market (0–10,000).
- Spectrum* Aggregate bandwidth available for mobile phone service by all operators in the market. Measured in MHz.

¹⁵ In particular, when spectrum allotments are equal across competitive licenses, we get $p(Q) = [1 + \frac{HHI}{\varepsilon(Q)}]^{-1} c(K, \frac{S}{N})$.

¹⁶ Fixed and mobile telephony services are not necessarily substitutes, so the sign of ρ is ambiguous.

TABLE 1 Descriptive Statistics

Variable	Obs	Mean	Standard Deviation	Minimum	Maximum
<i>TOTMIN</i> (millions/month)	452	2,972.59	8,345.29	129	78,338
<i>RPM</i> (US\$)	452	0.21	0.08	0.07	0.64
<i>HHI</i> (1–10,000)	452	3,785.49	1,036.26	1,648	6,458
<i>Spectrum</i> (MHz)	452	189.02	98.37	36.4	530
<i>Density</i> (hab./sq. kms.)	452	608.71	1,744.55	2.46	6,832.46
<i>Auction</i> (0-1)	452	0.70	0.46	0	1
<i>NotCPP</i> (0-1)	452	0.15	0.36	0	1
<i>GDPpc</i> (US\$/year)	452	18,332.42	9,543.31	2,007.14	38,551.03
<i>Fixprice</i> (US\$)	452	0.09	0.05	0	0.1999

Density A proxy for capital cost. Measured as mean inhabitants/square km.

Auction Dummy variable = 1 if wireless licenses awarded via auction; 0 otherwise.

NotCPP Dummy variable = 1 if the market *not* using *calling party pays* rule.

GDPpc Gross Domestic Product per capita in constant 2000 US\$.

Fixprice Mean price of 3 minute local fixed network peak period call in constant 2000 US\$.

Data, primarily from Merrill Lynch (2003), are quarterly from 1999I through 2003II for wireless telephone markets in 28 countries. Retail prices are proxied by mean revenue per minute of use for voice services (excluding data).¹⁷ The time series were incomplete for some countries, yielding unbalanced panel data. A detailed description of the sample is given in Appendix A. Summary statistics are displayed in Table 1.

(4) and (5) represent a system of equations in the endogenous variables $\ln(RPM)$ and $\ln(TOTMIN)$. Given a sample of countries and quarterly data, we initially ran a fixed-effects model to control for factors specific to the countries, such as population size and institutional differences. One problem encountered was that the variable *Fixprice* took the value zero in several countries (e.g., USA). To control for this truncation we introduced a dummy variable, *dumfix*, which takes the value of unity if the fixed line price is zero, and is otherwise equal to zero. Omitting *Fixprice*, we then included a variable defined as $(1 - dumfix) * \ln(Fixprice)$ as a regressor we labeled *Alfixprice*. Given that *dumfix* did not change within countries during the sample period, it was absorbed in the fixed-effects component. Likewise, the variables *Auction* and *NotCPP* dummies did not change over time for given countries, so in a standard fixed-effects model their role would be missed. Another issue involved the Herfindahl-Hirschman Index, which should not be considered exogenous. When additional spectrum is allocated, it is expected to negatively impact market concentration. We will return to this problem momentarily.

The estimation procedure adopted involves three stages. In the first, we perform a “within” transformation for unbalanced panel data. Then we run a standard 3SLS regression for the system of equations (4) (5) considering as endogenous variables $\ln(RPM)$, $\ln(TOTMIN)$, and $\ln(HHI)$. In the second, we use the residuals of the first stage to capture the effect of time-invariant variables (*NotCPP* and *Auction* dummies in our database), generating pseudo-fixed effects. In the third, we again perform a 3SLS procedure to estimate the system with the variables in levels, including the pseudo-fixed effects and time-invariant explanatory variables. The details are given in Appendix B. A summary of final results for different specifications of the model is given in Table 2. The upper part of the table corresponds to the mark-up equation and the lower to the demand equation.

¹⁷ “We calculate Revenue per Minute by dividing monthly *voice-only* ARPU [average revenue per unit] by MOU [minutes of use]. This RPM is not usually disclosed by operators, but we calculate it because we believe it is a good proxy for pricing.” Merrill Lynch (2003) (emphasis in original).

TABLE 2 Final Results for Different Specifications; model 6 is selected

DV: lrpm	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
	-2.448	2.891	0.489	0.034*	0.563	0.043*	0.618	0.042*	0.610	0.040*	0.614	0.039*
lrotrmin2	0.286	0.222										
lhhi	-162.561	92.616***	-18.886	4.593*	-24.442	5.400*	2.555	0.215*	2.505	0.194*	2.503	0.195*
lhhi2	10.346	5.849***	1.279	0.287*	1.630	0.338*						
lspectrum	-2.003	1.780	0.228	0.330	0.106	0.074	-0.046	0.064	-0.147	0.024*	-0.149	0.024*
lspectrum2	0.328	0.206	-0.012	0.032								
ldensity	-62.793	30.140**	-24.303	1.898*	-25.893	2.219*	-22.494	1.664*	-20.240	1.414*	-20.389	1.373*
ldensity2	5.518	2.651**	1.387	0.108*	1.458	0.124*	1.153	0.084*	0.878	0.062*	0.885	0.060*
lspecldcn	-0.216	0.131***	-0.048	0.015*	-0.046	0.016*	-0.023	0.015				
FEmarkup	0.640	0.306**	0.961	0.074*	0.991	0.083*	0.964	0.070*	0.962	0.067*	0.969	0.065*
notcpp	-42.063	20.067**	-0.087	0.083	0.283	0.104*	2.821	0.259*	5.787	0.445*	8.625	0.620*
auktion	5.917	2.732**	6.891	0.517*	7.436	0.614*	7.192	0.512*	7.423	0.505*		
constant	795.872	437.950***	133.248	21.910*	159.740	25.986*	39.839	2.984*	35.974	2.574*	41.095	2.741*
Number of obs.	452		452		452		452		452		452	
"R ² "	-5.659		0.609		0.536		0.607		0.612		0.612	

DV: lrotrmin	Demand Equation		Demand Equation		Demand Equation		Demand Equation		Demand Equation		Demand Equation	
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
lrpm	-0.200	0.439	-1.154	0.047*	-1.151	0.048*	-1.152	0.050*	-1.139	0.050*	-1.120	0.050*
lrpm2	0.295	0.140**										
lgdppc	11.039	0.360*	14.226	0.317*	13.395	0.315*	13.030	0.312*	12.852	0.310*	12.784	0.308*
lgdppc2	-0.459	0.022*	-0.675	0.019*	-0.617	0.019*	-0.596	0.019*	-0.586	0.019*	-0.582	0.019*
alfixprice	1.241	0.051*	1.516	0.044*	1.551	0.044*	1.789	0.044*	1.809	0.044*	1.804	0.044*
alfixprice2	0.265	0.014*	0.316	0.012*	0.323	0.012*	0.390	0.012*	0.397	0.012*	0.396	0.012*
FEdemand	1.001	0.011*	0.993	0.009*	0.994	0.009*	0.995	0.009*	0.995	0.009*	0.993	0.009*
notcpp	-3.340	0.102*	-3.340	0.066*	-3.437	0.067*	-3.605	0.068*	-3.606	0.068*	-3.586	0.068*
constant	-51.737	1.594*	-63.649	1.347*	-60.682	1.342*	-58.938	1.330*	-58.170	1.322*	-57.841	1.317*
Number of obs.	452		452		452		452		452		452	
"R ² "	0.970		0.975		0.975		0.975		0.975		0.976	

Note: "DV" stands for dependent variable. Significance: *1%, **5%, ***10%. "R²" is a pseudo-R² that can be less than 0.

Results for the preferred specification (model 6) are given in the last column and are referred to here.¹⁸ The model selection process is described in Appendix B.

The use here of fixed-effects panel data estimation could be challenged on various grounds. On the one hand, a totally pooled model is the simplest approach. Following Baltagi (2001), a direct application of an F-test (separately applied for the demand and mark-up equations) permits us to reject, at a 1% confidence level, the null hypothesis that the fixed effects are all the same.¹⁹ On the other hand, differences among countries could not be constrained to intercept terms and may make slopes “country specific.” The size of our panel is of insufficient scale to statistically reject this hypothesis.²⁰ We assume, as is often done, that a fixed-effects model is reasonable, supporting the assumption while improving the efficiency of our estimations by employing a pseudo-fixed-effects approach. This permits us to measure the effect of time invariant variables.

The pseudo-fixed-effects model constrains the interpretation of coefficient estimates driven primarily by cross-country variation. The slope estimates relied on to evaluate policy counterfactuals are produced with an embedded assumption that, after controlling for explanatory variables that include fixed effects and time-invariant variables, incremental impacts on equilibrium output (associated with, say, spectrum allocation changes) do not interact with those driven by other explanatory variables. A richer model capturing possible interactions would be desirable were data available.

Regression results, displayed in Table 2, appear reasonable. For instance, whereas the purpose of this exercise is not to measure the price elasticity of demand, the model’s estimate, -1.12 , is very close to estimates reported for the U.S. market.²¹ In addition, the estimated demand function exhibits a willingness to pay positively related to the GDP per capita, although at a decreasing rate. The total minutes demanded are increasing in the price of a local call using the fixed network (peak period), revealing a substitution effect between fixed and mobile services. A “not CPP” country exhibits, *ceteris paribus*, a reduction in the number of total minutes demanded. We note that this result conflicts with Crandall (2005).

The mark-up equation results suggest that the equilibrium price in the market increases with the Herfindahl-Hirschman Index but decreases with the amount of spectrum allocated to mobile services. These results are statistically significant, and are consistent with economic theory. It is expected that more competitive markets feature lower service prices, whereas expanded availability of radio spectrum lowers both fixed costs and variable operating expenses. Moreover, prices are decreasing in density, suggesting scale economies in the density dimension.

3. The role of spectrum policy

■ To evaluate the price and welfare effects of spectrum policies, the empirical results obtained are incorporated into a series of possible scenarios. The approach forecasts how prices and quantities in retail markets respond to regulatory changes. In this procedure, the coefficient estimates of greatest interest are those in the mark-up equation associated with *LHHI* and *LSPECTRUM*. These variables are directly affected by regulators.

The simulations follow the premise that the empirical model provides us with an estimated equilibrium and a 95% confidence interval within which the actual values should fall. Each

¹⁸ Some squared terms were dropped from the reported specification because they were not significant at conventional levels. Particularly important was the statistically insignificant effect of the interaction between spectrum and density in the mark-up equation.

¹⁹ Another option is a random-effects model, but we discard it because it is possible that we are omitting some explanatory variables that might be correlated with the included ones. In such a case, it is well known that OLS and random-effects models are biased and inconsistent (Cardellicchio, 1990).

²⁰ An alternative estimation that would allow different slopes between countries is Zellner’s SUR approach or the Conniffe (1982) extension. We do not have sufficient degrees of freedom to pursue these procedures. However, there are some advantages to using panel data methods. For example, we can control for country-level heterogeneity, we can improve efficiency, and we can measure effects that are undetectable in pure cross-section or pure time-series data.

²¹ Ingraham and Sidak (2004) estimate U.S. cellular elasticity of demand between -1.12 and -1.29 .

equilibrium forecast is computed until it achieves stability. Then we estimate a confidence interval based on Hotelling's T^2 statistic. We also report a bootstrapped 95% confidence interval for the sake of comparison. Simulations were performed in 1000 groups of 1000 cases each, with shocks to the system of equations coming from a bivariate normal distribution with mean zero for each component, and the variance-covariance matrix estimated from the stage 3 residuals explained in Appendix B. These experiments were conducted at least a hundred times to adjust the estimation; results were very stable.

□ **Equilibrium effects.** To perform price-quantity simulations, we adopted a "country-like" approach, where we fixed the exogenous variables at their sample values for the particular country in a specific period, and then varied the quantity of spectrum (in MHz) available to the mobile telephony sector. The estimated model derived in the previous subsection was then used to predict the effect on price and quantity.

The lower part of Table 3 displays a graph with simulated results in the United Kingdom in the first quarter of 2000, just before the assignment of 3G licenses (allocated 140 MHz of radio spectrum) via auction. It includes a 95% confidence interval. Price is decreasing in the amount of allocated spectrum, with the rate of decrease declining. Simulated retail prices are reduced because marginal costs fall with more abundant inputs and because the endogenous Herfindahl-Hirschman Index declines with more abundant spectrum. Similar simulations for other countries are reported below.

□ **Welfare effects.** We may now evaluate changes in social welfare associated with incremental spectrum allocations. In our country-like scenario, we estimate the impact on potential consumer surplus and license revenues related to a policy that exogenously increases the spectrum allocated to the market in 20, 80, 140, and 200 MHz increments. We assume that the bandwidth increments are utilized for mobile phone services.²²

The welfare change resulting from spectrum policy depends on four stochastic variables, initial and final prices, and quantities. In the simulations we assume a multivariate normal distribution. Instead of using an analytic solution for the marginal distribution of this probability function, we simulate the behavior in the neighborhood of each equilibrium and then compute the change in surpluses. These differences then yield the resulting welfare change.

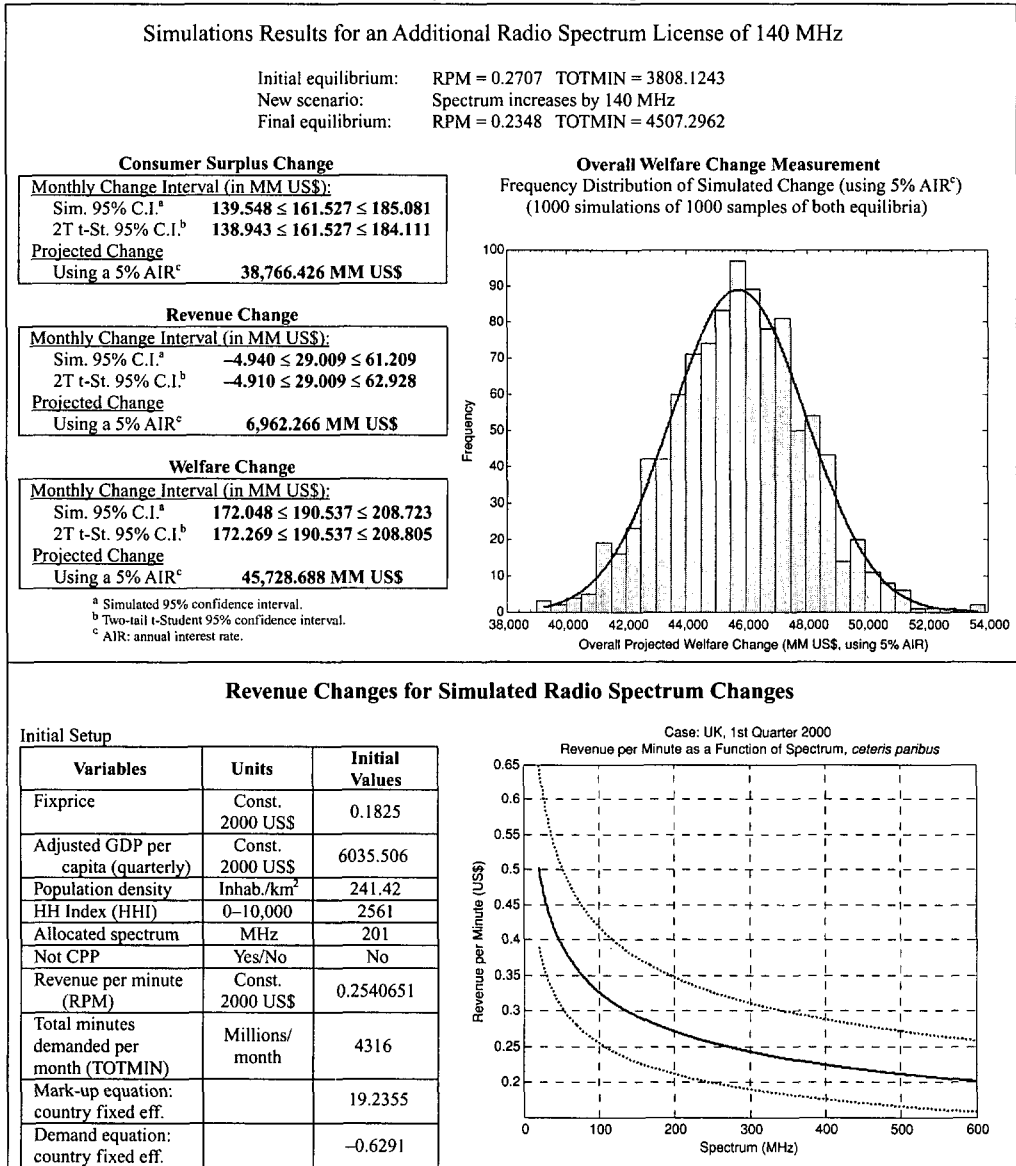
Expanded spectrum availability tends to cause industry concentration to decline. Take the U.S. case. The cellular telephone market was originally a duopoly, with 50 MHz of allocated spectrum split equally between the two licenses (per market). Then, personal communication services (PCS) licenses were auctioned in 1995 and 1997; the PCS licenses were, in aggregate, allocated 120 MHz. The additional bandwidth facilitated entry; by 2000, there were six competing national networks.²³

In the simulations, additional spectrum reduces predicted *HHI* according to the endogenous relationship derived from the empirical model. This, however, may well underestimate the effect of spectrum on concentration (or deconcentration) due to the models fixed effects and the multi year lags involved in the *HHI-SPECTRUM* relationship. During the sample period, for example, U.S. *HHI* fell as new networks expanded using PCS licenses auctioned years before, even as the United States did not award any additional mobile phone licenses during the 1999I–2003II sample period. Conversely, several countries awarded 3G (third-generation) licenses

²² This is a conservative assumption driven by data availability. The use of the new bandwidth to supply innovative wireless services would predictably increase welfare by a larger increment.

²³ One of the national networks, Nextel, utilized approximately 15 MHz allocated to specialized mobile radio (SMR) licenses. This constitutes a reinforcing example of new spectrum allocations yielding additional competition. On the formation of Nextel (*nee* Fleet Call) using SMR licenses, see Hazlett (2001). Conversely, the 120 MHz allocated to PCS licenses was not fully available to mobile carriers until 2005. That was when a dispute over so-called PCS C-block licenses, allocated 30 MHz, was resolved. See Roy Mark, "FCC Opens NextWave Spectrum Auction," *Internet News* (January 26, 2005).

TABLE 3 Simulation Scenario for a Country Like the United Kingdom, 1st Quarter 2000



during 2000 and 2001, yet new 3G deployments only became operational, with rare exceptions, starting in 2004.²⁴ The impact of network launches on *HHI* generally play out over several years.

It is likely that our sample, covering 4.5 years, is too short to adequately capture the lagged relationship. (Our attempt to estimate long lags produced coefficients that were not statistically significant.) If we are correct, the welfare estimates produced by our model should be interpreted as lower bounds for the social value of making additional radio spectrum available to network operators, a caveat reinforced by the exclusion of new services from the valuation estimates.

²⁴ There were 61 3G networks launched by December 2004. The first 2 began in Japan in October 2001 and December 2002. The next 12 were launched in 2003. "3G/UMTS Commercial Deployments," http://www.umts-forum.org/servlet/dycon/zumts/umts/Live/en/umts/Resources_Deployment_index (visited November 5, 2005).

FIGURE 1

EFFECT ON CONSUMER SURPLUS, REVENUES, AND WELFARE OF INCREASES IN SPECTRUM ALLOCATION (IN A COUNTRY LIKE THE UNITED KINGDOM, 1st QUARTER 2000)

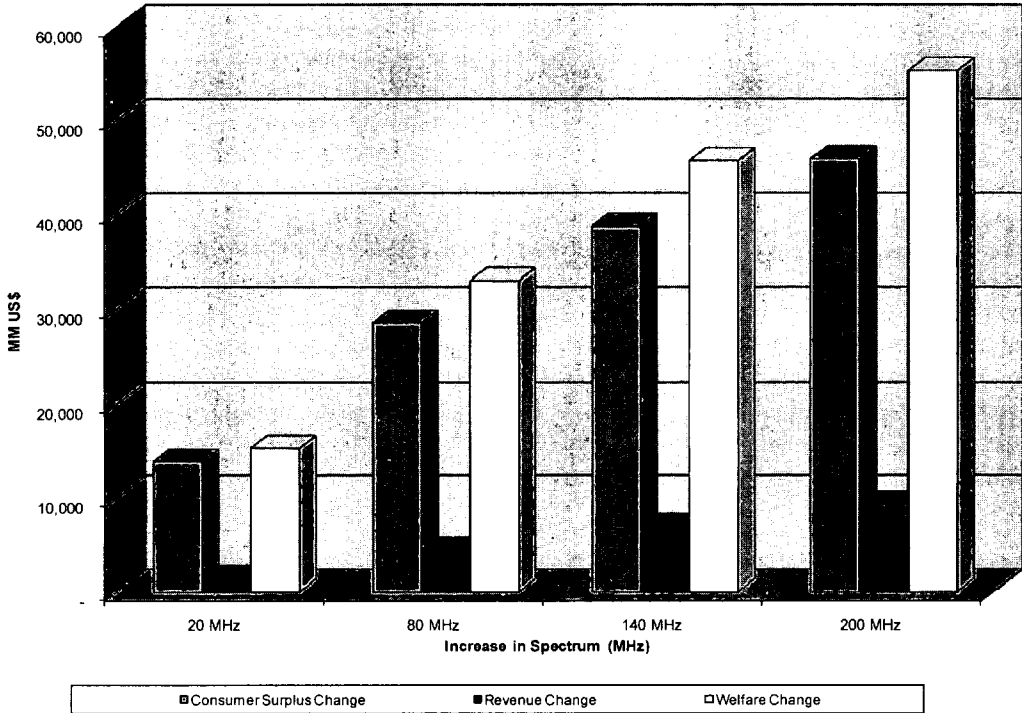


Table 3 and Figure 1 display results for a simulation approximating conditions found in the United Kingdom in the first quarter of 2000 (1Q00) when “The Biggest Auction Ever”²⁵ began. Licenses allocated 140 MHz of spectrum, matching the aggregate UK allocation, are assumed to be auctioned in our simulation. The British 3G licenses sold for approximately \$34 billion; applying the \$0.33 per-dollar public financing bonus implies social gains of about \$11.3 billion. Our simulation suggests, in comparison, that about \$39 billion in consumer surplus gains were realized from the 140 MHz of radio spectrum being made available to operators.²⁶ This increase in surplus dominates the benefits associated with tax efficiency. This outcome is illuminating precisely because the British 3G auctions are widely considered to be the most successful example of license rent extraction.

Alternatively, consider the U.S. market for wireless telephony. Using parameters obtained in our cross-country pricing model, we simulate an increase of 60 MHz in spectrum allocated for mobile telephony (on a base of 170 MHz). This is associated with a decline in retail prices of about 8%. A price drop of this magnitude is, in turn, associated with an increase in consumer surplus of about \$8.8 billion annually.

²⁵ As Ken Binmore and Paul Klemperer referenced it in the title of their 2002 article.

²⁶ In Table 3, I we first report the estimated monthly impact on consumer surplus, revenues, and welfare of additional spectrum allocations. Then we obtain annual effects and consider them as perpetuities which should be discounted, at some rate, to obtain net present values. The annual interest rate (AIR) used for this purpose is 5% per year, as shown in the table. This can be thought of as a real social discount rate. Because growth is expected for many years in wireless phone markets, it is not implausible that even if the (gross) discount rate is 10%, that a net discount rate of 5% (reflecting anticipated growth of 5%) would be appropriate.

TABLE 4 Summary of results for Belgium and Greece

	Units	Belgium	Greece
Auction date		2001/Q1	2001/Q3
Extra license	(MHz)	35.4	35
Change in price scenario 1	(%)	-4.42%	-3.36%
Change in MOU scenario 1	(%)	5.19%	3.91%
Change in price scenario 2	(%)	-1.43%	-1.09%
Change in MOU scenario 2	(%)	1.63%	1.23%
DCS1	US\$ MM	-2,236.60	-2,975.51
Standard deviation DCS1		362.66	555.87
DCS2	US\$ MM	-1,336.20	-1,926.24
Standard deviation DCS2		373.11	568.84
REV	US\$ MM	408.92	434.96
Social value of REV	US\$ MM	136.31	144.99

Given marginal license valuations of about \$150 million per nationwide MHz,²⁷ the capitalized value of nationwide licenses allocated 60 MHz is about \$9.1 billion.²⁸ If the public finance dividend applies, the tax efficiency gain of approximately \$3.0 billion is projected to be just one third the *annual* consumer gains associated with increased output. A delay of just 5 months swamps the public financing bonus altogether.

Reservation prices in Belgium and Greece. Of Belgian and Greek auctions held in 2001, Klemperer (2002a) writes: "Both countries held auctions for four licenses—and in each case attracted only the three incumbents, who therefore obtained licenses at the reserve prices which yielded about 45 Euros per capita in each case. It is very hard to argue plausibly that an auction deterred much entry when a license goes unsold, and there is also no obvious reason to criticise the reserve prices that these governments chose."

Our model helps analyze these arguments. Reserve prices do help to increase auction receipts, but the incremental revenue is not without social cost. The spectrum allocated to unsold licenses reduces operator efficiency and, perhaps, market competitiveness. Whereas the latter implies that network entry would have occurred if the license were priced below the reserve level, the former does not. In this example, if each incumbent's license were allocated 1/3 the bandwidth allocated the fourth,²⁹ lower marginal and capital costs would have resulted.

In Table 4 and Figure 2 we show the effect of withholding a license by the use of reserve prices in Belgium and Greece. In these simulations, details of which are given in Appendix C, we assume either

- (i) an entrant, at license price = 0, materializes, builds a competing network, and generates the endogenous decrease in *HHI* captured by our model; or
- (ii) no rival enters, but spectrum allocated the 4th license is utilized by incumbents, as the *HHI* yet remains constant.³⁰

²⁷ In September 2006, the FCC's advanced wireless services (AWS) auction yielded \$13.7 billion for licenses allocated 90 MHz nationwide. This implies valuation of about \$152 million per MHz. This auction involved the first new allocation of spectrum for mobile licenses following PCS (2G), and can be considered an approximation of marginal license value for the base period calibrating our estimates. March 2008 auction prices for licenses allocated 700 MHz spectrum were about twice as high on \$price/MHz/pop basis. The UHF airwaves allocated in the latter auction were thought to yield generally superior propagation characteristics.

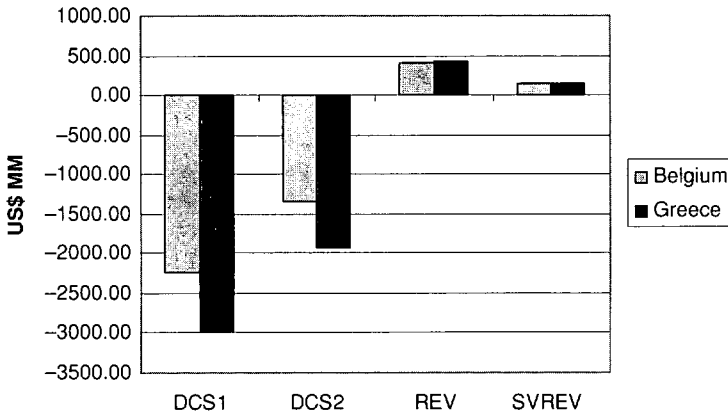
²⁸ These are present values, not flows. Licenses, once assigned to high bidders, are then renewed without competitive bidding so long as the licensees comply with regulatory rules.

²⁹ Contrarily, the Greek regulator promised to withhold the license for a minimum of 5 years in the event no qualifying bids were received.

³⁰ The simulations with *HHI* constant were also based on the results for model 6 reported in Table 2, but we considered only the direct effect of the extra spectrum assignment over the mark-up equation and, as a result, over the equilibrium.

FIGURE 2

WELFARE EFFECT OF WITHHOLDING A LICENSE IN BELGIUM AND GREECE



The change in consumer surplus estimated under the 1st (new entrant) scenario is DCS1 (delta consumer surplus, scenario 1); the estimated change in consumer surplus under the 2nd (spectrum reallocation) scenario is DCS2. These changes, negative given that spectrum is being withheld by the reserve price policy, are compared to the positive welfare effects associated with auction revenues. Here we conservatively attribute all receipts to the reserve price and assume that one third of government license revenues (REV) constitute social savings (SVREV).

Unsurprisingly, the spectrum withholding losses are greater when it is assumed that a new carrier enters the market at license reserve price = 0 (i.e., $|DCS1| > |DCS2|$ for both the Belgian and Greek markets). This implies that the spectrum, abstracting from the cost of complementary capital infrastructure, is used most efficiently by an entrant. The comparison of interest is between either DCS estimate and SVREV. Focusing on DCS1, consumer surplus losses from the reserve policy are about 15–20 times the magnitude of expected public financing gains in Belgium or Greece. This implies that *giving away* the licenses to facilitate competition between four rivals would have produced at least an order of magnitude more social welfare than restricting entry via the reserve policy.

Under the assumption that no new network would have been induced to enter at a license price of zero, welfare gains (DCS2) from spectrum redistribution among the incumbents also exceed those available from the reserve policy. The magnitude of this difference is still large (around one order of magnitude). However, the policies are not incompatible. Reserve prices could be utilized in an auction where spectrum allocated to unsold licenses is reallocated for the use of license winners.³¹ Auction rules imposed without this provision result, as in this instance, in the unproductive withholding of both licenses and spectrum. The reserve policy gives economists ample reason for criticism.

It is of note that the Greek 3G auction employed a two-stage procedure. In the first stage, firms bid for a “basic” 3G license that granted the use of 25 MHz. Winners in the first stage were then permitted to bid for extra bandwidth. In this second stage, reserve prices were much reduced. Of the three winners (the three 2G incumbents) in stage 1, one acquired licenses allocated another 20 MHz, another acquired licenses allocated 10 MHz, and the third did not bid the reserve price (and acquired no further 3G spectrum rights). This is evidence that the marginal demand for

³¹ This might, or might not, raise license bids, as the productive effects of the higher bandwidth to a particular license winner (raising value) would be at least partly offset by the increased bandwidth available to rivals (lowering value). See Hazlett (2008b).

TABLE 5 Welfare Costs of Weak Bidder Subsidies in U.S. PCS C-block Auctions

Year	Initial Estimated Equilibria			Final Estimated Equilibria			Welfare Changes	
	RPM		HHI 0–10,000	RPM		HHI 0–10,000	Annual	Accumulated
	Constant 2000 US\$	TOTMIN mill./month		Constant 2000 US\$	TOTMIN mill./month		Welfare Change Const. 2000 Bill. US\$	Welfare Change Const. 2000 Bill. US\$
1997	0.1888	27,276	1,664	0.1807	28,727	1,631	8.02	8.02
1998	0.1848	29,909	1,729	0.1769	31,500	1,694	8.65	16.68
1999	0.1813	32,902	1,788	0.1736	34,652	1,751	9.25	25.93
2000	0.1775	35,619	1,856	0.1699	37,514	1,819	9.87	35.79
2001	0.1734	36,306	1,949	0.1660	38,237	1,910	9.81	45.61
2003	0.1662	39,909	2,115	0.1591	42,032	2,071	10.37	66.08

bandwidth by one of three incumbents was relatively modest.³² It does not, however, imply that the social value of such bandwidth was zero. Our simulation suggests, in fact, that an additional 35 MHz of spectrum, if equally divided among the three incumbents, would substantially reduce retail prices and expand output. This is evidence of the divergence between consumer surplus gains and license values.

Subsidizing weak bidders in U.S. PCS auctions. Finally, consider the PCS C-block auctions that concluded in May 1996. U.S. regulators extended bidding credits to small businesses and rural telephone companies, granting qualified (that is, weak) bidders below-market interest rates on 10 year loans. The PCS C licenses were allocated 30 MHz of nationwide radio spectrum.

Bidding for licenses was intense; C-block winners committed to paying more than twice the price paid by winners of similar A and B licenses the previous year, after netting out bidding credits (Hazlett and Boliek, 1999). Yet, service was not provided for a decade; in fact, bids generally went uncollected. The great majority of licensees quickly declared bankruptcy, effectively or explicitly defaulting on long-term obligations to the federal government. A lengthy legal battle ensued to determine ownership of the licenses.³³ Through 2004, allocated spectrum—nearly one sixth the total bandwidth allocated to mobile phone service—went largely unused.

Our empirical model can be used to estimate the cost of this loss of bandwidth in the wireless telephone market. If cellular carriers had utilized another 30 MHz of radio spectrum, consumer welfare over the 7 year period, 1997–2003, would have increased by an estimated \$67 billion (using constant 2000 dollars). See Table 5.³⁴ This loss easily exceeds any plausible public financing gains from the auction design mechanisms under discussion.

The term “fiasco” has been applied to auction regimes that generate relatively low bids, but we see the FCC bidding preferences as more deserving of the term. Ironically, these

³² The bandwidth sold in the second stage (which was identical to the first-stage bandwidth, because spectrum segments were only actually positioned on the spectrum subsequent to the auction) had a reserve price which was just 1/10th as much per MHz; one of the firms which paid the reserve price for the basic license was unwilling to buy this additional spectrum, whereas the two other firms which paid the reserve price for the basic license were prepared to bid only a tiny bit more than 1/10th of the basic spectrum cost for additional spectrum.

³³ The federal government effectively lost this battle. Bankrupt parties succeeded in both retaining rights to their FCC licenses and in reducing the obligations owed the federal government. In mid-2004, a negotiated settlement was finally achieved with the largest C-block licensee, Nextwave. In January and February 2005, an FCC auction reassigned C-block licenses returned to the FCC for debt satisfaction.

³⁴ In Table 5 for each year between 1997 and 2003, we simulate the corresponding annual welfare change if an additional spectrum allocation of 30 MHz had occurred in that year. Differently from Table 3, we do not consider a perpetual benefit stream, limiting the estimated effects to a 7 year delay. This was actually a low-end estimate; the PCS C-block was ready for auction in 1994, yet licenses were not ultimately assigned until 2005. The 1994–1996 lag was due to the administrative chore of devising bidding credits and an auction structure at the FCC; 1996–2005 was spent undoing the results of those mechanisms that had made market deployments unachievable.

preferences serve the economics literature as a *paradigmatic example* of how to intensify bidding via policies to assist weak operators: “Partially subsidizing disadvantaged bidders, generally, more than compensates for the cost of the subsidy due to increased aggressiveness by first-line bidders” (Rothkopf, Harstad, and Fu, 2003). This conclusion follows from an analysis that is “complementary to Ayres and Cramton (1996),” which found “that a subsidy policy can sometimes materially benefit the bid taker” (Rothkopf, Harstad, and Fu, 2003). Specifically, Ayres and Cramton found that FCC bidding credits generated net revenues in a 1994 auction. The overwhelming loss of welfare associated with the 1996 PCS bidding credits did not enter their policy analysis or many of those to follow. Although the government’s credit policies proved faulty,³⁵ the salient fact for welfare analysis of spectrum allocation policy is that any rule favoring less efficient providers entails expected costs.³⁶ These costs are properly included in the welfare analysis.

4. Conclusion

■ Auctions are generally superior to alternative rights-assignment mechanisms such as beauty contests or lotteries.³⁷ Wireless license auctions appear to assign licenses to the most efficient network operators, and to have limited certain forms of rent dissipation. Yet, auction rules that focus on revenue extraction may conflict with the goal of maximizing social welfare.

Although revenue gains from enhanced competitive bidding are registered as leading directly to increase efficiency in offsetting activity-distorting taxes, the costs of such policies are often ignored. This is seen in frequent proposals recommending the use of reserve prices and bidding credits for inefficient wireless providers, as well as in the omission of time value when comparing alternative policy regimes.

Using a panel data set involving 28 countries and quarterly data from January 1999 to June 2003, we identify primary determinants of social welfare in mobile telephony markets. We find that the amount of allocated spectrum and the degree of market competitiveness are key drivers of retail market outcomes. Each is heavily influenced by government regulation. Policies that increase competition and permit wireless markets to operate more efficiently³⁸ empirically dominate social gains from license rent extraction.

The role of *ex post* market interaction in auction design has been studied (Caillaud and Jehiel, 1998; Das Varma, 2002; Jehiel, Moldovanu and Stacchetti, 1999; among others). However, the focus of that literature is on how externalities affect the bidding process and how a revenue-maximizing seller should adjust auction mechanisms. In contrast, our focus here is on welfare-maximizing public policy.³⁹

³⁵ Then-FCC Chairman Michael Powell believed that, as reported in the trade press, “the FCC learned its lesson from the NextWave/C-block debacle and will no longer auction off licenses using installment payments.” Heather Forsgren Weaver, “NextWave Must Shed Most of Its Spectrum under FCC Settlement.” *RCR Wireless News*. (April 20, 2004).

³⁶ Ayres and Cramton (1996) discuss the possibility that licensees will default on long-term debt obligations, but dismiss its empirical significance: “If a designated bidder defaulted, the government could easily foreclose and resell the licenses, but their resale value would be uncertain.”

³⁷ Prior to competitive bidding for FCC licenses in the United States, auctions constituted a controversial policy reform. One of the authors of this article participated in the policy debate, writing in favor of auctions (Thomas, Hazlett, “Making Money out of the Air,” *NY Times* [December 2, 1987]; Hazlett, “Dial ‘G’ for Giveaway,” *Barron’s* [June 4, 1990]).

³⁸ One important set of issues not investigated in our model pertains to technology mandates. Competition between competing wireless telephone standards (as in the United States) may produce better technology (e.g., Code Division Multiple Access) and more intense rivalry. See Gandal, Salant, and Waverman (2003).

³⁹ Welfare considerations have been discussed in auction theory, but as a side effect. For example, McAfee (1998) points out that, in the presence of interaction in a final market and under some plausible circumstances, the entrants could have advantages, in front of the incumbents, to win an auction for capacity. As a result, auctions do not have to be detrimental for consumers. The underlying idea is, at most, that maximization of auction revenues is not always in conflict with social welfare. Caillaud and Jehiel (1998) discuss the case of a welfare-maximizing seller; however, in their article, welfare is identified with an optimal allocation among bidders, and externalities beyond bidders are not considered.

The standard “spectrum auction” analysis points to the “embarrassingly low revenue in The Netherlands,” for example, as indicating public policy failure (Wolfstetter, 2001; citing Klemperer). Yet, it might also be noted that the Dutch have succeeded in making 355 MHz available for wireless phone operators—more than any other EU country. Alternatively, U.S. regulators made (counting generously) just 190 MHz of bandwidth available for mobile phone operators (Kwerel and Williams, 2002) through 2005, an outcome that merits little academic attention despite the *bona fide* fiasco it delivers in terms of lost wealth.

To be clear, our analysis does *not* imply that more efficient auction mechanisms yield little or no social gain. Historically, competitive bidding has, as advertised, saved social resources otherwise consumed by wasteful rent seeking (Hazlett and Michaels, 1993; Congressional Budget Office, 1997). Looking forward, were policymakers to deploy combinatorial auctions, as developed by several scholars (Cramton, Shoham, and Steinberg, 2006, for example), license assignments could be further improved. License auctions are a substantial contribution to economic policy, and economists productively contribute to their implementation. At a more general level, creating and assigning spectrum property rights in ways that economize on transaction costs continues to be the essential challenge for policymakers (Faulhaber, 2005; Hazlett, 2008a).

What this analysis fundamentally aims to achieve is a balanced approach to spectrum policy. Competitive bidding mechanisms are not exogenous to market outcomes when they alter the structure, capacity, timing, or firm composition of the wireless sector. Hence, policy instruments employed to extract revenues may alter social welfare in other dimensions. These incremental changes result from regulatory choices and are properly incorporated when evaluating alternative spectrum regimes.

Appendix A

■ **Mobile Voice Market Database.** Our main source of information was “Global Wireless Matrix 2Q03: Quarterly Update on Global Wireless Industry Metrics,” Merrill Lynch Global Securities Research & Economics Group, Global Fundamental Equity Research Department. This includes quarterly data for the wireless market in 46 countries, fourth quarter 1998 through second quarter 2003. All data were obtained from this source except the following:

Spectrum, Auction: The main source is each country’s telecommunications regulator and Communications Ministry. The Economist Intelligence Unit ViewsWire database, the European Commission, and the European Radio Communications Office are secondary sources.

GDPpc: The World Bank’s World Development Indicators (WDI) database, 2008. Values expressed in constant 2000 US\$.

GDP Deflator: Base year 2000. The World Bank’s World Development Indicators database, 2008. All monetary variables have been reexpressed in constant 2000 US\$ using this deflator.

Density: Constructed as population/area, where population is from Merrill Lynch and area is from the World Bank’s World Development Indicators 2003.

Fxprice: Taken from the International Telecommunications Union’s World Telecommunications Indicators 2002 database and then expressed in 2000 constant US\$.

Our sample is composed of all observations in the Merrill Lynch database for which we have data for all the relevant variables from the first quarter in 1999 through the second quarter in 2003. (Although Merrill Lynch data begin in fourth quarter 1998, the data listed in that quarter are very incomplete.) Our sample included the following 28 countries:

Argentina	Denmark	The Netherlands
Australia	Finland	New Zealand
Austria	France	Norway
Belgium	Germany	Portugal
Brazil	Greece	Singapore
Canada	Hong Kong	Spain
Chile	Hungary	United Kingdom
Colombia	Ireland	United States
Czech Republic	Italy	Venezuela
	Mexico	

Note that of the 46 countries in the Merrill Lynch database, many could not be used due to missing data (for variables not included in the ML database). The most difficult data to identify included *Spectrum* and *Fixprice*. To enable the inclusion of additional country data, *Fixprice* was adjusted in Canada: the reported values are zero from 1991 to 1994; thereafter it is not reported. We used an assumed value of “0” after 1994.

Appendix B

■ **Technical Notes.** Here we explain the estimation and simulation procedures used to derive the estimates discussed in this article. This note explains the basic system of estimated equations, the procedure for estimating HHI endogenously, model selection, and the way the simulations are developed.

□ **System of simultaneous equations.** Given that our initial goal is to identify the variables that should be included in an empirical welfare analysis of spectrum policy, we pose a general equilibrium described by the system of equations introduced in Section 2:

Mark-up equation:

$$p(Q) = \left[1 + \frac{HHI}{\varepsilon(Q)} \right]^{-1} \sum_{i=1}^N s_i c(K, \phi, S) \tag{A1}$$

Demand equation:

$$Q = \lambda Y^\delta F^\alpha p^\epsilon \tag{A2}$$

We do not have the necessary data to construct the cost function $c(\cdot)$. Instead we treat cost as an implicit function of capital (proxied by density) and total spectrum known at certain *loci* by an empirical approximation that includes linear and quadratic terms. In the estimations we are then able to statistically define the underlying functional form.

The theoretical model motivates the explanatory variables we use in each empirical equation. The empirical mark-up equation contains the main theoretical variables, including quadratic terms to capture nonlinear effects. In addition, a cross-term is also included to capture the implicit empirical approximation of $c(\cdot)$. The empirical demand equation is an expanded log-transformed version of the theoretical one. The initial model we estimate is given by the following system of equations:

Empirical mark-up equation:

$$\begin{aligned} \ln(RPM_{it}) = & \alpha_0 + \alpha_1 \ln(Q_{it}) + \alpha_2 [\ln(Q_{it})]^2 + \alpha_3 \ln(HHI_{it}) + \alpha_4 [\ln(HHI_{it})]^2 \\ & + \alpha_5 \ln(Spectrum_{it}) + \alpha_6 [\ln(Spectrum_{it})]^2 + \alpha_7 \ln(Density_{it}) + \alpha_8 [\ln(Density_{it})]^2 \\ & + \alpha_9 [\ln(Spectrum_{it}) * \ln(Density_{it})] + \alpha_{10} Auction_{it} + \alpha_{11} NotCPP_{it} + \eta_{it} \end{aligned}$$

Empirical demand equation:

$$\begin{aligned} \ln(Q_{it}) = & \beta_0 + \beta_1 \ln(RPM_{it}) + \beta_2 [\ln(RPM_{it})]^2 + \beta_3 \ln(GDPpc_{it}) + \beta_4 [\ln(GDPpc_{it})]^2 \\ & + \beta_5 \ln(Fixprice_{it}) + \beta_6 [\ln(Fixprice_{it})]^2 + \beta_7 NotCPP_{it} + \varepsilon_{it} \end{aligned}$$

where variables are defined in Section 2.

□ **HHI Endogeneity.** The behavior of *HHI* depends on spectrum allocations, the expected revenue per minute, the magnitude of demand (mainly total minutes demanded per time period), and other determinants. Hence, there is a two-way relationship between *HHI*, *RPM*, and *Q* (*TOTMIN* in what follows). These relationships pose an estimation problem that can be dealt with in different ways, assuming that entrants are permitted under spectrum allocation rules. In this article, we assume that *HHI*, *RPM*, and *TOTMIN* have an intrinsic, statistically significant relationship, and accordingly *HHI* should be included in the system of equations as an endogenous variable determined together with *RPM* and *TOTMIN* in the equilibrium.

□ **Estimation procedure.** We estimate a system of two simultaneous equations using a one-way fixed-effects panel data model, enhanced to improve efficiency. The method has three stages:

Stage 1: Simultaneous equations fixed-effects panel data model. We follow the basic approach posed by Cornwell, Schmidt, and Wyhowski (1992) for estimating a simultaneous equations model with panel data and an unobservable individual effect in each structural equation. To do this, we first perform a “within” transformation for unbalanced panel data, following Baltagi (2001). Then we estimate a 3SLS model with the transformed variables. We use an “unstructured” variance-covariance matrix in the estimation to allow heteroskedastic error structure and simple autocorrelation behavior.⁴⁰

⁴⁰ This is a reasonable and simpler way to deal with error structure avoiding the data-consuming HAC (heteroskedasticity-autocorrelation consistent) variance-covariance matrix estimation.

Tests reveal that this procedure is sufficient for the problem we investigate (Wooldridge, 2002). The regressions exclude *NotCPP* and *Auction* because they are time invariant and the “within” transformation omits them.

We also have to consider that in all the specifications considered at least *HHI* is also endogenously determined, so we instrument it with other variables (see Table B1, first stage, for all the auxiliary regressions in models 1–6). As a consequence, in these estimations, there are at least three endogenous variables in the first stage of the 3SLS procedure: *RPM*, *TOTMIN*, and *HHI*. In the third stage, however, there are only two equations: *RPM* and *TOTMIN*; *HHI* enters once in *RPM* (see Table B2 for a summary of results). These estimations yield the simultaneous equations fixed-effects panel data estimators.

Stage 2: Pseudo-fixed effects, and time-invariant and rarely changing variables. In this stage we apply the idea developed by Plümper and Troeger (2007), called fixed-effects vector decomposition (FEVD), which lets us improve the efficiency of our estimation through the inclusion of time-invariant and rarely changing variables. Given that we make a “within” transformation to our data in the previous stage, we were not able to include variables that are constant (within countries) over time, such as *NotCPP* and *Auction*. These variables contain substantial information, however, and the Plümper-Troeger technique allows us to capture this. To include these variables, we take the average residuals from stage 1, and run two auxiliary regressions:

$$\hat{u}_i^{Markup} = \delta_0 + \delta_1 NotCPP_i + \delta_2 Auction_i + v_i$$

$$\hat{u}_i^{Demand} = \varphi_0 + \varphi_1 NotCPP_i + \omega_i,$$

where u_i is calculated as an average over the corresponding time period for each country i .

Once we estimate these equations we obtain the estimated or pseudo-fixed effects through simple differentiation, so the mark-up and demand equations pseudo-fixed effects corresponds to \hat{v}_i and $\hat{\omega}_i$, respectively. These pseudo-fixed effects have zero mean. The results of the regressions and the estimated pseudo-fixed effects are contained in Table B3 for all the specifications reported in Table 2.

Stage 3: Fitting pooled OLS model. Up to now we have obtained a consistent (not necessarily the most efficient) estimator for our simultaneous equation fixed-effects panel data model, and we adjust the estimation to fit time-invariant and rarely changing variables. Now we perform the last stage to improve efficiency. The reasoning is simple: if the inconsistency problem posed by the panel data OLS models is associated with the unobservable factors contained in the fixed effects, we can include the pseudo-fixed effects together with the variables in levels (say, with no “within” transformations) to obtain an improved estimation.⁴¹ Furthermore, we can use 3SLS to estimate the whole system of equations. The results of the first stage of that procedure are reported in Table B4.

A summary of final results (third stage) for different specifications is reported in Table 2 in Section 2. Via this procedure, we obtain the estimators used throughout the article. More detailed estimation outputs are available from the authors.

□ **Model selection.** We start our estimations with the general specification posed at the beginning of this appendix (leading to model 1). There we observe symptoms of multicollinearity that, through successive restricted model tests (also called Chow tests, or F-tests), were sequentially discarded. This procedure allowed us to statistically evaluate alternative specifications, permitting selection of the suitable model in such a way that avoids an arbitrary model specification. It is important to note, however, that all the specifications considered are theoretically consistent with the model developed in Section 2, because the theoretical mark-up equation is, by definition, consistent with the existence of nonlinear terms, and a generalized demand equation can contain quadratic terms, to capture nonlinear effects, without conflicting with theoretical properties of demand functions at least in the rank considered for the variables.

Final results for some of the estimated specifications are contained in Table 2, while the intermediate steps are reported in Tables B1–B4.

□ **Simulation procedures.** The key results in this article derive from simulated scenarios. Given that our interest is in quantifying the effects of different policies in given countries and time periods, we use the “model 6” specification and estimated parameters to perform simulations. In a typical simulation we assume that, in some specific country and period, more spectrum is made available for network operators, so the endogenous variables *RPM*, *TOTMIN*, and *HHI* respond to such a policy. The results follow the premise that the empirical model provides us with an estimated final equilibrium and a confidence interval within which the observed situation should fall.

Because our database contains monthly information, a direct simulation generates monthly figures. We translate those numbers into annual numbers and then we assume a net 5% discount to obtain net present values. In some situations we report those net present values, whereas in others it seems relevant to look at the annual effects.

⁴¹ According to Baltagi (2001), when the true model is fixed effects an OLS estimation “yields biased and inconsistent estimates of the regression parameters. This is an omission variables bias due to the fact that OLS deletes the individual dummies when in fact they are relevant.”

TABLE B1 Stage 1: The Internal First-Stage Regressions

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
DV: lrpmdev												
Ispectrumdev	0.327	0.322	0.327	0.322	-0.062	0.074	-0.062	0.074	-0.131	0.027*	-0.131	0.027*
Ispectrum2dev	-0.038	0.030	-0.038	0.030	-11.422	1.683*	-11.422	1.683*	-10.399	1.339*	-10.399	1.339*
Idensitydev	-11.755	1.703*	-11.755	1.703*	0.166	0.184	0.166	0.184	0.033	0.127	0.033	0.127
Idensity2dev	0.185	0.184	0.185	0.184	-0.016	0.016	-0.016	0.016				
IspecIdendev	-0.017	0.016	-0.017	0.016	2.533	3.117	2.533	3.117	2.374	3.113	2.374	3.113
Igdppcdev	1.589	3.206	1.589	3.206	-0.091	0.202	-0.091	0.202	-0.078	0.201	-0.078	0.201
Igdppc2dev	-0.028	0.208	-0.028	0.208	4.231	1.182*	4.231	1.182*	4.159	1.180*	4.159	1.180*
alfxpricedev	4.330	1.184*	4.330	1.184*	0.791	0.264*	0.791	0.264*	0.772	0.264*	0.772	0.264*
alfxprice2dev	0.809	0.265*	0.809	0.265*	0.020	0.008**	0.020	0.008**	0.020	0.008**	0.020	0.008**
constant	0.020	0.008**	0.020	0.008**	452		452		452		452	
Number of obs.	452		452		452		452		452		452	
R ²	0.525		0.525		0.523		0.523		0.522		0.522	
Adj R ²	0.515		0.515		0.515		0.515		0.515		0.515	
DV: ltotmindev												
Ispectrumdev	-1.581	0.314*	-1.581	0.314*	-0.113	0.074	-0.113	0.074	0.120	0.027*	0.120	0.027*
Ispectrum2dev	0.143	0.030*	0.143	0.030*	16.734	1.682*	16.734	1.682*	13.270	1.355*	13.270	1.355*
Idensitydev	17.992	1.663*	17.992	1.663*	-0.567	0.184*	-0.567	0.184*	-0.116	0.129	-0.116	0.129
Idensity2dev	-0.640	0.180*	-0.640	0.180*	0.054	0.016*	0.054	0.016*				
IspecIdendev	0.059	0.015*	0.059	0.015*	8.924	3.116*	8.924	3.116*	9.459	3.149*	9.459	3.149*
Igdppcdev	12.485	3.130*	12.485	3.130*	-0.392	0.202***	-0.392	0.202***	-0.434	0.204**	-0.434	0.204**
Igdppc2dev	-0.630	0.203*	-0.630	0.203*	-3.242	1.182*	-3.242	1.182*	-2.998	1.194**	-2.998	1.194**
alfxpricedev	-3.617	1.156*	-3.617	1.156*	-0.580	0.264**	-0.580	0.264**	-0.513	0.267**	-0.513	0.267**
alfxprice2dev	-0.647	0.258**	-0.647	0.258**	-0.020	0.008*	-0.020	0.008*	-0.019	0.008**	-0.019	0.008**
constant	-0.018	0.008**	-0.018	0.008**	452		452		452		452	
Number of obs.	452		452		452		452		452		452	
R ²	0.714		0.714		0.699		0.699		0.691		0.691	
Adj R ²	0.708		0.708		0.694		0.694		0.687		0.687	

(Continued)

TABLE B1 (Continued.)

DV: lhhidev	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
lspectrumdev	0.318	0.138**	0.318	0.138**	0.026	0.032	0.026	0.032	-0.046	0.012*	-0.046	0.012*
lspectrum2dev	-0.028	0.013**	-0.028	0.013**								
lidentitydev	-0.439	0.732	-0.439	0.732	-0.189	0.726	-0.189	0.726	0.876	0.581	0.876	0.581
lidentity2dev	-0.137	0.079***	-0.137	0.079***	-0.151	0.079***	-0.151	0.079***	-0.290	0.055*	-0.290	0.055*
lspecidende	-0.018	0.007*	-0.018	0.007*	-0.016	0.007**	-0.016	0.007**				
lsgdppcdev	0.250	1.379	0.250	1.379	0.958	1.345	0.958	1.345	0.793	1.351	0.793	1.351
lsgdppc2dev	-0.050	0.089	-0.050	0.089	-0.097	0.087	-0.097	0.087	-0.084	0.087	-0.084	0.087
alfxprice2dev	2.435	0.509*	2.435	0.509*	2.360	0.510*	2.360	0.510*	2.285	0.512*	2.285	0.512*
alfxprice2dev	0.491	0.114*	0.491	0.114*	0.478	0.114*	0.478	0.114*	0.457	0.114*	0.457	0.114*
constant	-0.002	0.003	-0.002	0.003	-0.001	0.003	-0.001	0.003	-0.002	0.003	-0.002	0.003
Number of obs.	452		452		452		452		452		452	
R ²	0.442		0.442		0.436		0.436		0.428		0.428	
Adj R ²	0.430		0.430		0.426		0.426		0.419		0.419	
DV: lhhi2dev	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
lspectrumdev	5.024	2.310**	5.024	2.310**	0.312	0.529						
lspectrum2dev	-0.458	0.218**	-0.458	0.218**								
lidentitydev	-4.366	12.218	-4.366	12.218	-0.328	12.111	-0.328	12.111				
lidentity2dev	-2.485	1.323***	-2.485	1.323***	-2.721	1.323**	-2.721	1.323**				
lspecidende	-0.269	0.113**	-0.269	0.113**	-0.253	0.114**	-0.253	0.114**				
lsgdppcdev	6.701	23.000	6.701	23.000	18.130	22.430	18.130	22.430				
lsgdppc2dev	-0.980	1.492	-0.980	1.492	-1.742	1.452	-1.742	1.452				
alfxprice2dev	39.344	8.497*	39.344	8.497*	38.143	8.510*	38.143	8.510*				
alfxprice2dev	7.886	1.898*	7.886	1.898*	7.672	1.903*	7.672	1.903*				
constant	-0.031	0.057	-0.031	0.057	-0.024	0.057	-0.024	0.057				
Number of obs.	452		452		452		452		452		452	
R ²	0.439		0.439		0.434		0.434		0.428		0.428	
Adj R ²	0.428		0.428		0.423		0.423		0.419		0.419	

(Continued)

TABLE B1 (Continued.)

DV: lrpm2dev		Other Auxiliary Regressions for Model 1		DV: ltothmin2dev	
	Coef.	SD		Coef.	SD
lspectrumdev	-1.572	1.125	lspectrumdev	-21.661	4.852*
lspectrum2dev	0.167	0.106	lspectrum2dev	1.789	0.459*
ldensitydev	39.449	5.950*	ldensitydev	273.857	25.670*
ldensity2dev	-0.112	0.644	ldensity2dev	-12.288	2.779*
lspecldev	0.046	0.055	lspecldev	1.092	0.238*
lgdppcdev	5.981	11.202	lgdppcdev	112.324	48.323**
lgdppc2dev	-0.633	0.727	lgdppc2dev	-4.805	3.134
alfixpricedev	-13.502	4.138*	alfixpricedev	-52.882	17.851*
alfixprice2dev	-2.588	0.925*	alfixprice2dev	-9.077	3.988**
constant	-0.063	0.028**	constant	-0.290	0.119**
Number of obs.	452		Number of obs.	452	
R ²	0.491		R ²	0.671	
Adj R ²	0.480		Adj R ²	0.664	

Note: "DV" stands for dependent variable. Significance: *1%, **5%, ***10%. "R²" is a pseudo-R² that can be less than 0.

TABLE B2 Stage 1: The Internal Third-Stage Regressions

DV: Irpm	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Mark-Up Equation											
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
lrotrmdev	-10.967	22.387	0.505	0.223**	0.572	0.236**	0.633	0.218*	0.627	0.218*	0.627	0.218*
lrotrm2dev	0.920	1.787										
lhhidev	-199.885	363.629	-19.189	17.995	-21.932	18.816	2.537	0.748*	2.511	0.751*	2.511	0.751*
lhhi2dev	12.707	22.884	1.297	1.080	1.471	1.131						
lspectrumdev	2.626	4.899	1.014	0.504**	0.218	0.163	0.058	0.101	-0.083	0.049***	-0.083	0.049***
lspectrum2dev	0.024	0.283	-0.078	0.045***								
lidentitydev	-98.849	146.744	-25.319	4.484*	-26.149	4.676*	-23.381	3.936*	-21.141	3.577*	-21.141	3.577*
lidentity2dev	8.778	14.637	1.451	0.383*	1.479	0.399*	1.206	0.320*	0.923	0.263*	0.923	0.263*
lspecdendev	-0.458	0.819	-0.058	0.030**	-0.058	0.031***	-0.033	0.022				
constant	0.114	0.171	0.033	0.013*	0.036	0.014*	0.037	0.013*	0.036	0.013*	0.036	0.013*
Number of obs.	452		452		452		452		452		452	
"R ² "	-31.028		-0.094		-0.207		-0.080		-0.070		-0.070	

DV: lrotrm	Demand Equation											
	Demand Equation											
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
lrotrmdev	-0.665	0.604	-1.205	0.068*	-1.182	0.067*	-1.173	0.067*	-1.166	0.067*	-1.166	0.067*
lrotrm2dev	0.147	0.172										
lrgdppcdev	11.497	3.757*	14.762	3.359*	13.889	3.335*	13.443	3.290*	13.275	3.280*	13.275	3.280*
lrgdppc2dev	-0.487	0.240**	-0.705	0.214*	-0.646	0.213*	-0.620	0.210*	-0.610	0.209*	-0.610	0.209*
alfxprice2dev	1.240	1.364	1.505	1.181	1.548	1.170	1.788	1.153	1.810	1.148	1.810	1.148
alfxprice2dev	0.265	0.292	0.311	0.265	0.320	0.263	0.388	0.258	0.395	0.256	0.395	0.256
constant	0.004	0.009	0.005	0.009	0.005	0.008	0.004	0.008	0.004	0.008	0.004	0.008
Number of obs.	452		452		452		452		452		452	
"R ² "	0.625		0.625		0.635		0.638		0.641		0.641	

Note: "DV" stands for dependent variable. Significance: *1%, **5%, ***10%. "R²" is a pseudo-R² that can be less than 0.

TABLE B3 Stage 2: Regressions with Time-Invariant Variables and Pseudo-Fixed Effects

DV: uimarkup	Regressions Including Time-Invariant and Almost-Time-Invariant Variables																	
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6							
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD						
notcupp	-68.001	27.674**	-0.173	12.734	0.225	13.307	2.811	12.787	5.918	12.851	8.806	12.247						
auktion	8.862	20.735	7.162	9.541	7.494	9.970	7.438	9.581	7.700	9.629								
_cons	1046.140	16.393*	135.122	7.543*	150.037	7.882*	41.968	7.574*	38.082	7.612*	42.895	4.629*						
Number of obs.	28	28	28	28	28	28	28	28	28	28	28	28						
R ²	0.197	0.024	0.024	0.024	0.024	0.031	0.031	0.044	0.044	0.044	0.020	0.020						
Adj R ²	0.132	-0.055	-0.055	-0.054	-0.054	-0.046	-0.046	-0.033	-0.033	-0.033	-0.018	-0.018						
DV: uideemand	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD						
notcupp	-3.295	1.515**	-3.382	1.478**	-3.469	1.500**	-3.633	1.476**	-3.639	1.470**	-3.639	1.470**						
_cons	-53.942	0.573*	-66.055	0.559*	-62.857	0.567*	-60.759	0.558*	-60.048	0.556*	-60.048	0.556*						
Number of obs.	28	28	28	28	28	28	28	28	28	28	28	28						
R ²	0.154	0.168	0.168	0.171	0.171	0.189	0.189	0.191	0.191	0.191	0.191	0.191						
Adj R ²	0.121	0.136	0.136	0.139	0.139	0.158	0.158	0.160	0.160	0.160	0.160	0.160						

(Continued)

TABLE B3 (Continued.)

Country	Estimated Pseudo-Fixed Effects											
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Mark-Up Equation	Demand Equation	Mark-Up Equation	Demand Equation	Mark-Up Equation	Demand Equation	Mark-Up Equation	Demand Equation	Mark-Up Equation	Demand Equation	Mark-Up Equation	Demand Equation
Argentina	-47.789	1.547	-22.728	1.414	-23.676	1.487	-22.292	1.487	-22.072	1.486	-19.185	1.486
Australia	-170.084	-1.439	-58.382	-1.386	-60.644	-1.410	-56.311	-1.356	-53.686	-1.346	-50.798	-1.346
Austria	25.244	-2.593	6.941	-2.455	7.215	-2.506	6.553	-2.451	6.053	-2.442	8.941	-2.442
Belgium	35.243	-2.654	18.380	-2.579	19.252	-2.613	18.483	-2.558	18.573	-2.547	21.461	-2.547
Brazil	-31.345	5.530	-17.109	5.416	-17.934	5.479	-17.181	5.289	-17.278	5.253	-14.391	5.253
Canada	-83.411	-0.177	-53.328	-0.338	-55.796	-0.331	-54.406	-0.321	-55.291	-0.314	-55.291	-0.314
Chile	-19.608	2.003	-9.155	1.839	-9.455	1.928	-8.821	1.920	-8.659	1.919	-13.472	1.919
Colombia	1.418	6.236	-0.535	6.370	-0.516	6.377	-0.533	6.135	-0.673	6.080	-5.485	6.080
Czech	28.937	2.699	9.713	2.485	10.115	2.560	9.315	2.565	8.906	2.564	11.794	2.564
Denmark	30.635	-3.813	9.988	-3.564	10.438	-3.645	9.723	-3.601	9.279	-3.596	12.166	-3.596
Finland	-38.452	-2.803	-14.976	-2.701	-15.581	-2.736	-14.627	-2.684	-14.210	-2.673	-19.023	-2.673
France	31.228	-0.533	14.376	-0.428	14.941	-0.462	14.002	-0.419	13.810	-0.412	8.997	-0.412
Germany	33.603	-0.490	16.001	-0.316	16.630	-0.361	15.714	-0.325	15.585	-0.321	18.473	-0.321
Greece	22.701	-0.589	5.190	-0.604	5.382	-0.581	4.792	-0.582	4.269	-0.583	7.157	-0.583
Hungary	24.885	2.987	7.247	2.803	7.551	2.881	6.831	2.860	6.363	2.854	9.250	2.854
Ireland	15.460	-3.258	5.390	-3.133	5.594	-3.189	5.206	-3.131	4.966	-3.120	0.153	-3.120
Italy	28.318	0.020	13.191	0.038	13.695	0.028	12.749	0.079	12.513	0.089	15.400	0.089
Mexico	1.745	3.401	-3.310	3.193	-3.539	3.265	-3.818	3.273	-4.301	3.273	-1.413	3.273
Netherlands	37.336	-1.962	21.172	-1.818	22.145	-1.867	21.487	-1.815	21.743	-1.807	24.630	-1.807
New Zealand	-52.154	-3.510	-22.759	-3.971	-23.746	-3.988	-22.507	-4.149	-22.294	-4.150	-19.407	-4.150
Norway	-43.314	-4.146	-16.319	-3.742	-16.977	-3.875	-15.862	-3.828	-15.386	-3.824	-20.198	-3.824
Portugal	36.573	0.204	15.232	0.044	15.895	0.097	15.071	0.127	14.867	0.134	10.055	0.134
Singapore	22.398	-0.595	32.097	-0.425	33.890	-0.368	33.830	-0.397	36.028	-0.414	36.028	-0.414
UK	32.727	-0.752	16.463	-0.644	17.116	-0.696	16.462	-0.640	16.348	-0.629	19.235	-0.629
US	36.002	1.891	-11.448	1.968	-12.545	1.900	-14.325	1.905	-17.733	1.906	-17.733	1.906
Venezuela	-8.168	3.438	-4.538	3.302	-4.799	3.370	-4.618	3.341	-4.648	3.330	-9.461	3.330

Note: "DV" stands for dependent variable. Significance: *1%, **5%, ***10%.

TABLE B4 Stage 3: The Internal First-Stage Regressions

DV: lrpm	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
lspectrum	-1.001	0.400**	-0.688	0.386***	-0.119	0.072***	-0.167	0.073**	-0.289	0.028*	-0.285	0.028*
lspectrum2	0.080	0.039**	0.058	0.038								
ldensity	-1.692	0.488*	-4.395	0.634*	-4.336	0.617*	-2.820	0.520*	-2.447	0.470*	-2.884	0.431*
ldensity2	0.154	0.045*	0.253	0.038*	0.246	0.036*	0.143	0.028*	0.096	0.021*	0.116	0.019*
lspclden	-0.026	0.016	-0.040	0.015**	-0.038	0.015***	-0.028	0.015***				
FEmarkup	0.021	0.005*	0.186	0.025*	0.177	0.024*	0.133	0.023*	0.124	0.022*	0.144	0.020*
notcpp	-2.087	0.406*	-0.809	0.116*	-0.841	0.108*	-0.480	0.114*	-0.077	0.151	0.388	0.196**
auction	0.289	0.048*	1.374	0.171*	1.378	0.169*	1.058	0.158*	1.031	0.159*		
lgdppc	2.865	0.433*	3.150	0.424*	3.207	0.422*	3.347	0.431*	3.412	0.428*	3.666	0.415*
lgdppc2	-0.145	0.027*	-0.164	0.026*	-0.165	0.026*	-0.177	0.026*	-0.182	0.026*	-0.196	0.026*
alfixprice	0.131	0.085	0.156	0.077**	0.230	0.071*	0.191	0.073*	0.185	0.073**	0.241	0.069*
alfixprice2	0.033	0.022	0.037	0.020***	0.055	0.018*	0.051	0.019*	0.052	0.019*	0.064	0.018*
FEdemand	0.092	0.017*	0.104	0.014*	0.111	0.015*	0.096	0.015*	0.088	0.014*	0.101	0.013*
constant	-7.542	2.244*	-0.791	2.508	-2.665	2.321	-7.142	2.109*	-7.940	2.048*	-7.012	2.113*
Number of obs.	452		452		452		452		452		452	
R ²	0.587		0.621		0.616		0.600		0.598		0.593	
Adj R ²	0.575		0.610		0.606		0.589		0.587		0.584	

(Continued)

TABLE B4 (Continued.)

DV: Iotmin	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
Ispectrum	0.059	0.424	-0.278	0.424	0.076	0.078	0.130	0.079***	0.329	0.030*	0.320	0.030*
Ispectrum2	0.007	0.041	0.034	0.041	4.317	0.670*	2.666	0.563*	2.181	0.509*	2.999	0.473*
Idensity	1.640	0.517*	4.675	0.697*	-0.248	0.040*	-0.137	0.031*	-0.080	0.023*	-0.119	0.021*
Idensity2	-0.158	0.048*	-0.273	0.042*	0.057	0.016*	0.046	0.017*				
Ispeciden	0.048	0.017*	0.060	0.017*	-0.182	0.026*	-0.132	0.025*	-0.115	0.024*	-0.152	0.022*
FEmarkup	-0.022	0.005*	-0.202	0.028*	-2.500	0.127*	-3.033	0.124*	-3.421	0.163*	-3.950	0.214*
notcpp	-0.918	0.430**	-2.326	0.127*	-1.473	0.184*	-1.114	0.171*				
auktion	-0.358	0.051*	-1.556	0.188*	9.970	0.458*	9.426	0.466*	9.160	0.464*	8.684	0.455*
Igdppc	8.158	0.459*	10.745	0.466*	-0.442	0.029*	-0.406	0.029*	-0.388	0.028*	-0.362	0.028*
Igdppc2	-0.319	0.029*	-0.495	0.029*	1.306	0.077*	1.588	0.079*	1.622	0.079*	1.518	0.076*
alfixprice	1.025	0.090*	1.255	0.084*	0.262	0.020*	0.333	0.021*	0.340	0.021*	0.317	0.020*
alfixprice2	0.209	0.023*	0.250	0.022*	0.876	0.016*	0.894	0.016*	0.908	0.015*	0.884	0.014*
FEdemand	0.894	0.018*	0.878	0.016*	-56.704	2.521*	-49.958	2.280*	-48.164	2.218*	-49.333	2.316*
constant	-41.875	2.380*	-59.642	2.758*								
Number of obs.	452		452		452		452		452		452	
R ²	0.944		0.945		0.945		0.943		0.943		0.941	
Adj R ²	0.942		0.943		0.944		0.942		0.941		0.940	

(Continued)

TABLE B4 (Continued.)

DV: lhhl	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD	Coef.	SD
Spectrum	0.365	0.289	0.007	0.252	-0.052	0.047	-0.066	0.042	-0.130	0.016*	-0.127	0.016*
Ispectrum2	-0.035	0.028	-0.007	0.025								
Identity	4.489	0.353*	7.821	0.415*	7.704	0.400*	7.095	0.298*	6.614	0.271*	6.241	0.250*
Identity2	-0.377	0.032*	-0.443	0.025*	-0.430	0.024*	-0.364	0.016*	-0.295	0.012*	-0.278	0.011*
Ispeciden	-0.023	0.012**	-0.016	0.010	-0.017	0.010***	-0.014	0.009				
FEmarkup	-0.044	0.004*	-0.299	0.017*	-0.285	0.016*	-0.294	0.013*	-0.308	0.013*	-0.291	0.012*
notopp	3.045	0.294*	0.142	0.076***	0.118	0.070***	-0.573	0.065*	-1.526	0.087*	-2.324	0.114*
auction	-0.427	0.035*	-2.097	0.112*	-2.093	0.110*	-2.132	0.091*	-2.309	0.092*		
lignppc	-0.103	0.313	-0.577	0.277**	-0.620	0.274**	-0.975	0.247*	-0.862	0.247*	-0.644	0.241*
lignppc2	-0.028	0.020	0.009	0.017	0.008	0.017	0.029	0.015***	0.021	0.015	0.010	0.015
alfxprice	-0.275	0.062*	-0.220	0.050*	-0.274	0.046*	-0.278	0.042*	-0.291	0.042*	-0.243	0.040*
alfxprice2	-0.042	0.016*	-0.027	0.013**	-0.039	0.012*	-0.048	0.011*	-0.050	0.011*	-0.039	0.011*
FEdemand	-0.171	0.012*	-0.164	0.009*	-0.177	0.010*	-0.179	0.009*	-0.186	0.008*	-0.176	0.008*
constant	-1.052	1.624	-10.014	1.641*	-9.250	1.505*	-6.446	1.207*	-5.982	1.180*	-7.182	1.227*
Number of obs.	452		452		452		452		452		452	
R ²	0.612		0.709		0.711		0.764		0.760		0.754	
Adj. R ²	0.601		0.700		0.703		0.758		0.754		0.748	
DV: lhhi2												
Spectrum	5.987	4.709	0.223	4.119	-0.927	0.759						
Ispectrum2	-0.585	0.460	-0.128	0.401								
Identity	75.147	5.753*	129.131	6.768*	127.260	6.528*						
Identity2	-6.329	0.529*	-7.309	0.405*	-7.109	0.386*						
Ispeciden	-0.362	0.191***	-0.256	0.161	-0.276	0.160***						
FEmarkup	-0.737	0.061*	-4.939	0.271*	-4.711	0.253*						
notopp	51.061	4.785*	2.285	1.234***	1.893	1.147***						
auction	-7.134	0.567*	-34.622	1.830*	-34.577	1.788*						
lignppc	-2.376	5.103	-10.134	4.530**	-10.886	4.466**						
lignppc2	-0.427	0.319	0.193	0.278	0.177	0.275						
alfxprice	-4.444	1.005*	-3.444	0.819*	-4.347	0.749*						
alfxprice2	-0.679	0.259*	-0.413	0.214***	-0.620	0.194*						
FEdemand	-2.818	0.200*	-2.671	0.154*	-2.882	0.158*						
constant	-85.176	26.454*	-231.426	26.790*	-218.384	24.560*						
Number of obs.	452		452		452							
R ²	0.611		0.707		0.709							
Adj. R ²	0.600		0.698		0.701							

(Continued)

TABLE B4 (Continued.)

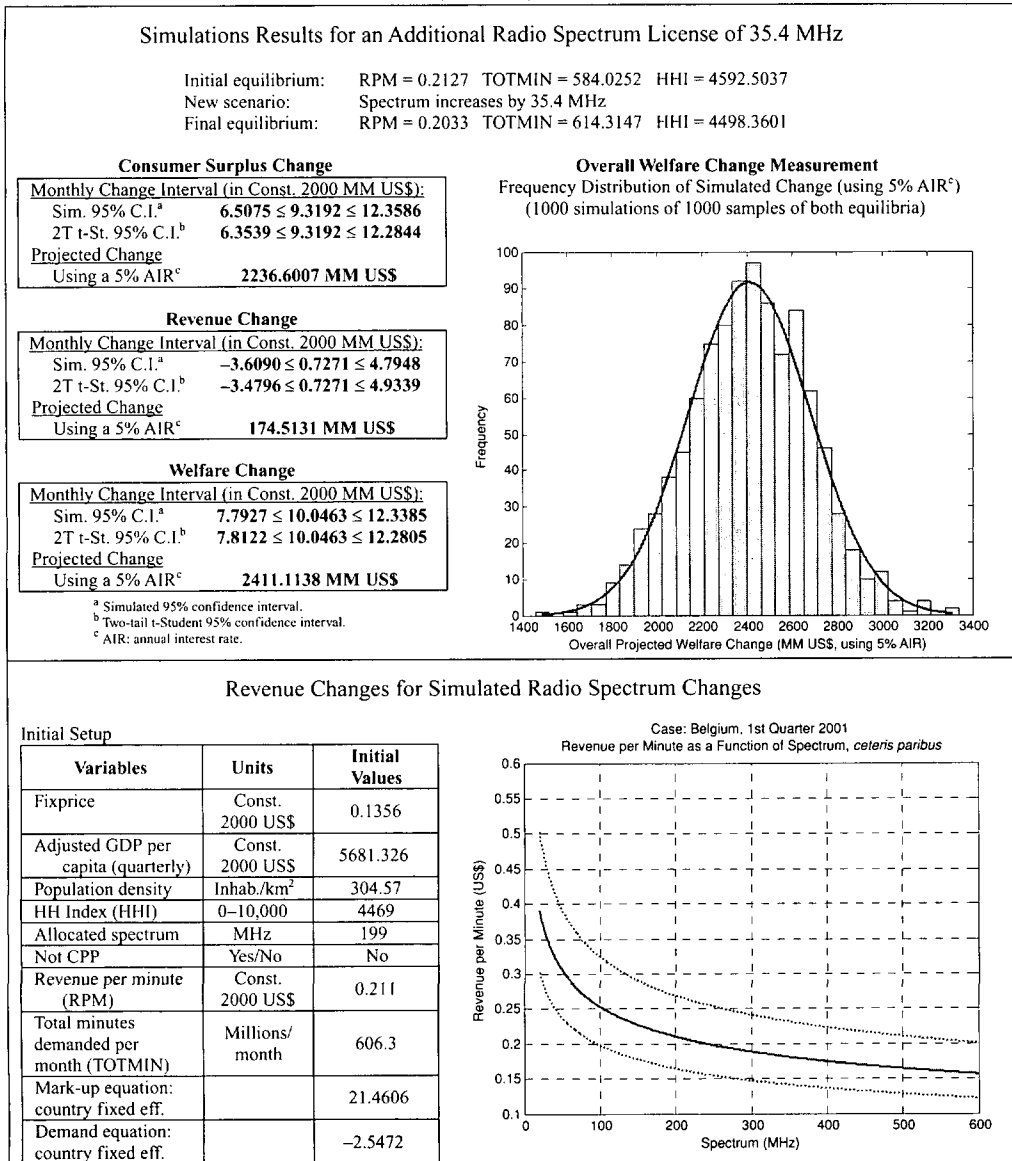
Other Auxiliary Regressions for Model I					
DV: Irpm2	Coef.	SD	DV: Itotmin2	Coef.	SD
Ispectrum	3.022	1.371**	Ispectrum	-0.525	6.634
Ispectrum2	-0.255	0.134***	Ispectrum2	0.083	0.647
Idensity	4.032	1.675**	Idensity	60.627	8.103*
Idensity2	-0.382	0.154**	Idensity2	-5.653	0.745*
Ispeciden	0.114	0.055**	Ispeciden	0.941	0.268*
FEmarkup	-0.054	0.018*	FEmarkup	-0.672	0.086*
notcpp	6.002	1.393*	notcpp	14.501	6.740**
auktion	-0.851	0.165*	auktion	-7.591	0.799*
lgdppc	-8.221	1.486*	lgdppc	110.210	7.188*
lgdppc2	0.404	0.093*	lgdppc2	-4.181	0.449*
alfixprice	-0.352	0.293	alfixprice	15.139	1.416*
alfixprice2	-0.096	0.075	alfixprice2	3.167	0.364*
FEdemand	-0.286	0.058*	FEdemand	12.561	0.282*
constant	22.017	7.703*	constant	-707.906	37.264*
Number of obs.	452		Number of obs.	452	
R ²	0.586		R ²	0.942	
Adj R ²	0.574		Adj R ²	0.940	

Note: "DV" stands for dependent variable. Significance: * 1%, ** 5%, *** 10%. "R²" is a pseudo-R² that can be less than 0.

Appendix C

Simulations for Belgium and Greece

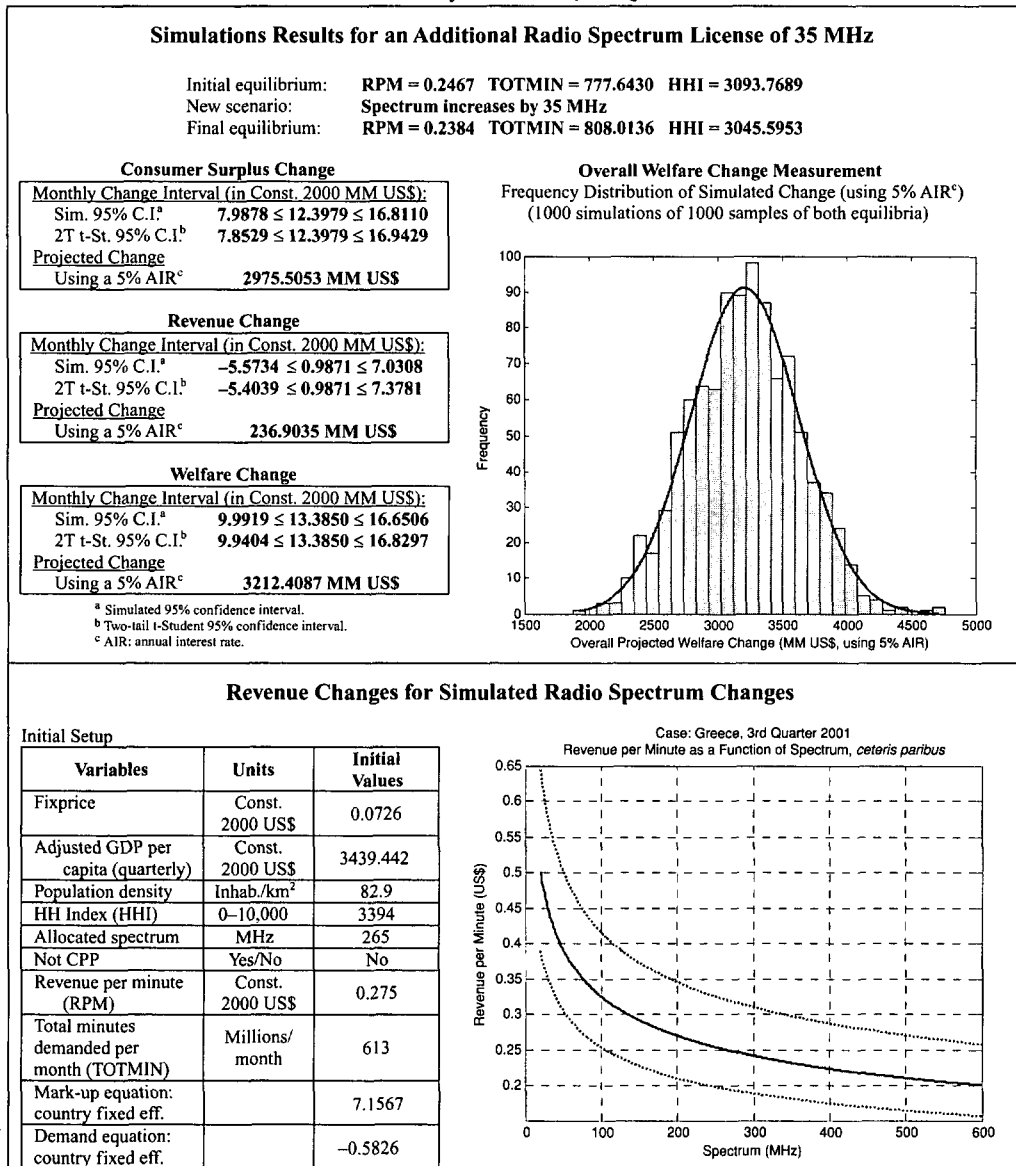
TABLE C1 Simulation Scenario for a country like Belgium, 1st Quarter 2001



Each equilibrium forecast is computed until it achieves stability.⁴² Then we estimate a confidence interval based on Hotelling's T² statistic. The distribution of the welfare change measurement is assumed to be a multivariate normal with four dimensions, two for price (RPM) and quantity (TOTMIN) in the starting equilibrium, and two for the corresponding variables in the final equilibrium. Instead of using an analytic solution for the marginal distribution of this probability function, we simulate the behavior in the neighborhood of each equilibrium and then compute the welfare change.

⁴² The stability criterion for convergence to a particular equilibrium compares, from one iteration to the next, the difference between iterated RPM and TOTMIN. We determine an equilibrium to exist when the maximum of either difference is no larger than 1.0e-07.

TABLE C2 Simulation Scenario for a Country Like Greece, 3rd Quarter 2001



Simulations were performed in 1000 groups of 1000 cases each, with shocks to the system of equations coming from a bivariate normal distribution with mean zero for each dimension, and variance-covariance matrix estimated from stage 3 residuals. These experiments were repeated at least one hundred times and produce stable results.

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