Regulatory Bias in the Price Structure of Local Telephone Service

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Abstract

This paper combines a discrete choice model of demand for residential local telephone service and a model of optimal price regulation to estimate the welfare weights that state regulators place on consumers with different incomes and locations. The methods employed allow for endogenous prices and use simulation to control for household-level differences in income and participation in subsidy programs. The results show that, while state regulators place a larger relative weight on low income consumers in rural areas, there is no evidence for a bias towards rural consumers on average. I also find that the relative weight on low income consumers is lower in poor areas, and that it is larger if the regulator is a Democrat or subject to direct election. I explore the welfare effects of replacing the observed price structure with (i) prices equal to marginal or average costs, (ii) prices that maximize unweighted consumer surplus and (iii) prices that recover the total cost of residential service. These alternative policies generally lead to reductions in telephone penetration among low income consumers, substantial redistribution of surplus from consumers to firms and fairly small increases in total welfare. The welfare gains are somewhat larger if geographic price discrimination is allowed.

KEYWORDS: Ramsey Prices, Regulatory Bias, Welfare Analysis, GMM, Simulation.

JEL classification: L51, L96, D61.

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1 Introduction

Residential access to the telephone network is a local service for which demand and cost conditions differ across the geography and the different social groups of the US. Optimal prices, which maximize total welfare given the constraints on the regulator, would vary as a function of these different market conditions. This class of second-best problems has been known at least since Ramsey (1927). Actual regulation can fall short of this ideal benchmark given information and legal constraints, but also given the bias of regulators in favor of particular groups of the regulated agents. This article estimates the implied welfare weights that state regulators place on the surplus of consumers with different incomes and geographic locations and it obtains a measure of the welfare effects of bias towards specific consumer groups.

Telecommunications and broadcasting account for 2.48% of US GDP.[1] Knowledge of the objectives of state regulators in Public Utility Commissions (PUCs) is important as they have kept their influence over the prices of intrastate wireline telephone services after the Telecommunications Act of 1996. These regulators can also be expected to play a role in the implementation of new regulation affecting Internet and wireless services. The design of a US National Broadband Plan (NBP) is underway and the role of the states in the implementation of the plan is presently debated.[2] The state commissions currently hold power over the eligibility of low income users of wireless services for subsidy programs and they may play a greater role in the future if regulation extends in the sector. Wireless telephone prices were regulated in a number of states before 1995 as described in Hausman (2002). The consolidation of major operators such as AT&T and Verizon might lead to the reintroduction of regulation.

A state telephone regulator is responsible for multiple local markets inside her given jurisdiction and, in principle, could set a different price for local telephone for each location and consumer group. In practice, state regulators divide their jurisdictions in a limited number of geographic zones for which they adopt homogenous pricing policies. In addition, non-geographic price discrimination is limited to discounted prices for low income consumers. The regulator is also constrained by the break even requirement of the firm. Given these restrictions and her own objectives, the state regulator will set

[1] This figure corresponds to the Bureau of Economic Analysis (BEA) Industry Accounts for year 2007. The GDP shares of other sectors with exposure to industrial regulation are 2.038% (Utilities), 0.243% (Waste Management), 2.949% (Transportation) and 7.904% (Finance and Insurance).

[2] The FCC launched the NBP in 2009 and a specific proposal is due to be presented to the Congress on February 2010. The NBP will include subsidies for firms and it is also possible that subsidies are extended to individuals. An specific policy considered is the extension of the Broadband loans of Rural Utility Services. See www.broadband.gov for developments.

prices. This paper rationalizes this decision into the problem of an optimizing regulator with a hybrid objective function that weights the sum of profits and consumer surplus. Acting on the public interest would require to weigh equally consumer surplus and profit to maximize total welfare. The private interest theory of regulation initiated by the seminal work of Stigler (1971) points to the possibility that regulation is not always guided by public welfare considerations. The private interest of regulators is a potential cause of the presence of systematic differences in the weights across different consumer groups. State regulators who put different weights on consumers as a function of their locations and incomes can favor certain consumer groups as long as the profit requirement of the firm is satisfied.

It has been a concern of academics and practitioners alike that the historical pricing structure of telecommunications included cross subsidies[3] across consumers (business versus residential, urban versus rural, high-income versus low-income). The main interest for economists in cross subsidies resides in the fact that they can potentially decrease social welfare as they disconnect prices and costs. A particular form of cross subsidy that lacks rigorous analysis is the possible transfer between urban and rural customers, as pointed out in Riordan (2002). Observation of tariffs for different geographic areas as in Riordan(2002) or Rosston and Wimmer (2005) reveals that telephone rates for rural areas are on average below average cost and lower than in corresponding urban areas. This observation alone is not enough to conclude that there is a different weight on urban and rural consumers as demand and marginal costs also differ across these areas.

The optimal regulation model allows me to formalize the pricing decision and separate neatly demand and cost factors affecting prices from regulatory bias. The combination of optimality conditions on prices with estimates of demand and cost allows me to infer the difference in the consumer weights used by the regulator. This formulation also enables the calculation of counterfactual price choices and welfare outcomes of alternative regulatory regimes. For example, it is possible to calculate the outcomes of policy changes that maximize total consumer surplus given the current level of deficit in residential telephone services (no bias in favor of specific consumer groups) or optimal prices given the obligation to keep a zero deficit. The method employed adapts the econometric framework of Berry, Levinsohn and Pakes (1995), henceforth BLP, to the study of regulated industries.

My demand estimation strategy uses a discrete choice model with simulation, popularized in the

[3] The term cross subsidy generally refers to price distortions originated by allowing losses for a subset of services A sustained by positive profits in subset B. Faulhaber (1975) provides a formal definition characterizing a price structure as subsidy-free if revenues do not exceed stand-alone costs for any subset of services. Palmer (1992) finds positive evidence of a subsidy from business to residential users.

empirical IO literature by BLP, to allow for different price sensitivity and participation in subsidy programs across income groups. I apply these methods to a broad cross section of data at the local market level. The resulting estimated average demand elasticities for the general population are low (0.02), although low income households, who are potential marginal adopters, exhibit higher average elasticities (0.054). The typical pattern of elasticities in each local market contains a flat close to zero elasticity for most of the population and a significantly higher elasticity for poor consumers. These results encompass the estimates in the existing literature analyzing the demand for telephone access with non-survey data.

I estimate different specifications of the regulatory problem that allow for different assumptions on the information of the regulator about costs and the financial burdens of subsidy programs for the states. The federal government funds price subsidies to customers who have a low income or are located in high cost areas. If the federal portion of price subsidies is not included as a cost in state budgets, an optimal regulator will set lower prices for the affected consumers even if she does not put a high weight on their welfare. I estimate scenarios with both full and partial internalization of the financial burden of the subsidy programs. For the cost assumptions, I consider first a regulator that forms a best estimate of marginal cost based on network characteristics (area, user distribution, etc.). I estimate this marginal cost with the use of engineering cost data. I check the robustness of the results with alternative assumptions that equate marginal with average cost or recover marginal cost exclusively from the first order conditions.

I find that the differences in consumer weights are systematically connected to differences in the percentage of rural and poor population. A higher percentage of rural population is seen to increase the weight in favor of the low income consumers across different models. On the contrary, there is no conclusive evidence to support that the general population of consumers is favored in rural areas. The effect of the percentage of poor population depends on the specification considered. If the federal funding of subsidy programs is internalized by state regulators, I find a high relative weight on low income consumers in geographic areas with high poverty. The result is reversed once the more realistic assumption of exclusion of federal costs from state budgets is incorporated. Political controls also turn significant in this latter specification with the percentage of democrats in the PUC and direct election associated to higher weights on low income consumers. This set of results shows the importance of using the appropriate institutional assumptions.

Counterfactual experiments examine first the alignment of prices with estimated marginal and average costs. I observe that the actual residential prices are generally below marginal cost with the resulting excess of variable costs over residential local telephone revenues (this residential deficit is covered by the profits of the firm in other sectors and regulatory subsidies). The change from actual to cost oriented prices leads then to a substantial transfer from consumers to firms ($8.5 B annually for marginal cost pricing). However, the adjustment in total welfare is moderate ($192 M annually for marginal cost pricing). Unless indirect efficiency gains are sizeable,[4] the redistributive consequences of the shift to cost oriented prices well exceed efficiency gains. An additional policy experiment considers the shift to prices maximizing unweighted consumer surplus given the constraint of maintaining the current deficit. This policy eliminates intra-consumer bias and it produces a transfer from low income consumers to the general population. Finally, I examine prices maximizing total welfare with the constraint of recovering the total cost of residential telephone service. The results of this experiment are close to the cost oriented pricing rules with reductions in low income telephone penetration, substantial redistribution from consumers to firms and moderate increases in total welfare. The welfare gains in these latter experiments are greatest if geographic price discrimination is allowed. These findings for demand and regulatory behavior relate to different branches of the literature on regulation and telecommunications demand that I review next.

Literature review

The demand for telephone access across the United States has been studied with aggregate data in a number of works including Hausman et al. (1993), Crandall and Waverman (2000), Ross et al. (1998), Garbacz and Thompson (2002) and Ackerbeg et al. (2008). An important motivation of these studies is measuring the sensitivity of demand for access to prices in order to evaluate the effect of federal and state subsidies to local telephone service. Hausman et al. (1993) use Federal Communications Commission (FCC) data on penetration aggregated over multiple local markets and conclude that there is a low elasticity of access to price. Ross et al. (1998) and Garbacz and Thompson (2002) find similar results with the use of state-wide data. For example, Garbacz and Thompson (2002) find own price elasticity in the range of -0.006 and -0.011, a value close to the -0.005 in Hausman et al. (1993). The use of aggregated data masks variation in local conditions and the aggregation of all consumers masks the possible differences in demand elasticity of different demographic groups. For example, descriptive analysis in Riordan (2002) documents the relation between local market telephone penetration and income level and race composition. Ackerberg et al. (2008) address these shortcomings with a sample

[4] For example, the increased residential telephone profits can be used to reduce general taxation.

at the local market level focused on poor households, who are more likely to have an homogenous price elasticity. Ackerberg et al. (2008) also control for the endogeneity of prices and subsidies. The current article contributes to this literature by considering how to control for the different price sensitivity of different consumers with aggregate data and introducing an explicit optimal regulation model for the endogenous choice of prices.

The use of discrete choice models with simulation to study markets for differentiated goods has become popular in the empirical IO literature following the work of BLP. This estimation framework is well known, with clear asymptotic properties of the estimator established in Berry, Linton and Pakes (2004). Applications are numerous, including examples such as Nevo (2000, 2001) and Ho (2006). A virtue of BLP is the ability to control for the effect on demand for a product of the interaction between consumer and product characteristics without the availability of individual consumer data. Particularly, the effect of prices on demand can depend on the distribution of individual income. This trait of BLP can also be a useful for the study of demand for regulated services, such as local telephone, as regulators and researchers often lack detailed survey data. The pioneering study of residential local telephone access by Taylor and Kreidel (1990) already considered the calculation of market demand from an aggregation of individual demands according to the distribution of income. However, the properties of the estimator used in that paper are not well known and it is not possible to perform inference on the price coefficients.[5]

A related strand of the literature studies demand for telephone services with survey data in articles such as Perl (1984), Train et al. (1987), Miravete (2002), Wolak (1996), and Economides et al. (2008). This survey data allows one to control directly for the effect of individual income and demographic characteristics. Additionally, the observation of individual usage and choices over price menus allows one to estimate not only the demand for access but also for the number of calls, duration, service plans. For example, Train et al. (1987) use a nested logit model that considers two separate choices over service plan and portfolio of calls, finding a low price elasticity of usage. Economides et al. (2008) use an alternative discrete-continuous demand model for choice of service plan and usage. This latter article finds that increased variety of pricing plans and product differentiation affect the value of service. Miravete (2002) studies the effect of usage uncertainty on plan choice and finds that consumers in his sample adopt on average the right decisions. Wolak (1996) uses survey data and a continuous demand model allowing for boundary solutions to study the effect of local and long distance prices

[5] Taylor (1994) Chapter 5.II summarizes the methods and results of this work. Standard errors are not available for a variety of coefficients of the model as shown in p. 103 of Taylor (1994).

on consumer welfare. The low average elasticity of usage in models estimating individual household demand suggests that the use of a single monthly fee is an adequate proxy for the cost of service. It remains the fact that even if the monthly cost is stable for each household, it can vary across households depending on their level of usage.

The telecommunications sector remains highly regulated despite the introduction of competition that I survey in the next section. The study of telecommunications regulation includes examples such as Ai and Sappington (2002), Ai, Martinez and Sappington (2004), Greenstein, McMaster and Spiller (1995), Rosston and Wimmer (2005) and Rosston et al. (2008). These empirical studies estimate the effect of different economic and political characteristics of the state on the behavior of regulators (price and quality choices) and the firm (investment). This literature connects with the early work of Joskow (1972, 1973) that studies the relation between the characteristics of the regulatory process and policy choices. The present work is closest to Rosston et al. (2008) as that article studies the effect of private interest groups on the structure of telephone prices (retail, business and wholesale) by estimating a price equations system that controls for demand, cost and political factors. The current article is focused on residential prices and it contributes to this literature with a structural approach that recovers information directly on the objective function of the regulator.

Related structural studies of regulation include Wolak (1994), Gagnepain and Ivaldi (2002) and Timmins (2002). Wolak (1994) estimates the production function of regulated water utilities and tests for the presence of private cost information. The model in Wolak (1994) assumes a regulator maximizing consumer surplus. Gagnepain and Ivaldi (2002) also focus on the estimation of the production function and private information of the firm.[6] Gagnepain and Ivaldi (2002) do not use the assumption of an optimizing regulator for estimation but they show how the optimal regulation model can be used to calculate counterfactual welfare levels of alternative regulation regimes. Timmins (2002) assumes a regulator maximizing a hybrid welfare function that allows for weight differences only between consumers and the firm. The main goal for this author is the recovery of forward-looking costs of water supply in California. I allow the weights on consumers to differ according to the demographic and political characteristics as this is my main objective.

The use of an optimal regulation model to separate welfare weights can be traced back to Ross

[6] Asymmetric information has been central in the new theory of regulation starting with Baron and Myerson (1982) and Laffont and Tirole (1986). Vuong and Perrigne (2004) represents a recent research effort to estimate a regulation model as in Laffont and Tirole (1986). I consider optimizing behavior on the part of the regulator but not optimal revelation mechanisms. The available information is assumed to depend on the exogenous regulatory process.

(1984). This article spanned a series of applications to different industries such as Morrison (1987), Kim (1995) and Knittel (2003). The results in these articles rely on calibration, preexisting estimates of demand and costs, or reduced form estimation. I estimate both the demand and the structural regulation models within a GMM framework that offers clear guidance for statistical inference.

The rest of the paper is organized as follows. Section 2 provides basic background on the local telephone sector. Section 3 provides a description of the data set. Section 4 presents the demand and regulation models. Section 5 builds the estimation procedure. Section 6 presents results. Section 7 introduces policy experiments. Section 8 concludes.

2 Local Telephone Network in the US: Basic background

The local telephone network ("local loop") is the combination of a wire center (or switching office) and connection facilities, which are operated by a local carrier firm. The wire center can direct signals (telephone calls) between different points in the local network and control the signal traffic into and out of it. The connecting plant joins the customer premises (households or businesses) to the wire center. The traffic between local networks is handled through a different type of connection facilities (long distance trunks). Gasmi et al. (2002) provide a more detailed technical description of the local telephone network. Local markets in the U.S., and elsewhere, have been typically served by a single firm called local exchange carrier (LEC) and subject to price and quality regulation. A single firm, AT&T, dominated the local markets and the long distance segment in the U. S. for most of the past century. However, the U.S. Telecommunications sector was also characterized by a progressive opening to competition. Brock (2002) and Woroch (2002) provide an excellent historical overview.

The presence of fixed cost elements in the local network creates returns of scale and scope that could render the duplication of the infrastructure socially undesirable.[7] Moderate competition might be necessary to sustain the system as the firms require mark ups over marginal cost of service to recover investment costs. Price regulation would allow prices high enough to sustain investment but would limit the exercise of monopoly power. A regulator of the industry could also be more capable of ensuring generalized access of the population to the Telecommunication network, a goal that can be termed

[7] The empirical literature has studied the issue with use of AT&T historical cost data, as in Evans and Heckman (1983) and Shin and Ying (1992), and cost data from engineering simulations, Gabel and Kennet (1994) and Gasmi, Laffont and Sharkey (1997). This latter work is more favorable to the presence of scale and scope economics and points out the limitations of historical data (technological change, high level of aggregation...).

as Universal Service [8]. The counterpoint to this positive view of regulation is the contention that a competitive regime can provide better incentives for allocative (lower demand distortions) and dynamic (investment in cost reduction) efficiency. The FCC, courts and legislators progressively adopted over the second half of the last century departures from the regulatory paradigm[9] that finally lead to a general revision of the regulatory system in the Telecommunications Act of 1996.

The Telecommunications Act (TA) of 1996 intended to provide the framework to make competition feasible in all the segments of the industry, including the local network, which had not been greatly affected by the advance of competition in the long distance segment and the introduction of mobile phones. The incumbent local carriers (ILECs) would be forced to compete with new competitive carriers (CLECs). The focus on competition of the TA of 1996 did not imply a reduction of the regulatory powers of the FCC or the State Regulators but a redefinition of objectives. The state regulators kept their authority over local retail prices and they were assigned the task to mediate between ILECs and CLECs in the pricing of wholesale access.[10] The power of state regulators over tariffs is founded on the evolution of administrative law in early twentieth century and the US Supreme Court jurisprudence[11] recognizing that regulated rates must be "just and reasonable", balancing the interests of consumers and investors. This legal powers extend to the new competence of state regulators over wholesale prices.

The historical rate structure of ILECs offers evidence in favor of an implicit system of cross subsidies between consumers groups (urban to rural consumers, business to residential consumers,etc.) as studied in Palmer (1992) or Rosston and Wimmer (2005). The introduction of competition would force the state regulators to rebalance their retail tariff structures as competitors would target the services with high regulated prices (business, urban areas) and erode the profit base that was the source of the

[8] Riordan (2002) highlights the ambiguity of the term. In the 1980's and 1990's the term applied to telephone services but it is likely to extend to Internet Broadband. In earlier parts of the XXth century it referred more modestly to a centralized system with broad geographical coverage.

[9] Starting in the 1950s, the FCC introduced competition into the equipment manufacturing and long distance segments. The resistance of AT&T to allow competition in long distance triggered in the 1970s an Antitrust Investigation of the Department of Justice (DOJ) that would conclude with the Modification of Final Judgment (1984,MOFJ). The MOFJ dictated the line of business separation between local and long distance telephone operations. The result was the creation of regional local operators (Baby Bells) separated from the long distance service offered by firms such as AT&T, MCI and Sprint.

[10] The TA 96 intended to facilitate competition by allowing potential entrants to lease the infrastructure (unbundled elements) of the ILECs to provide their own services. The ILECs were forced to provide access to the CLECs at prices set by state regulators under the guidelines of the FCC that favored a forward looking cost methodology. Litigation by ILECs lead to the adoption of the Review Remand Order (2004) by the FCC with an upward revision of the prices of unbundled elements.

[11] *Federal Power Commission v. Hope Natural Gas (Hope) in 320 U.S. 591 (1944)* and *Bluefield Water Works & Improvement Co. v. Public Service Commission of West Virginia in 262 U.S. 679 (1923).* Gifford (2003) provides a brief overview of the legal framework.

subsidies. This analysis of competition dates back at least to Faulhaber (1975) and it appears in contemporary work such as Riordan (2002) and Rosston et al.(2008).

Data from Kaserman and Mayo (2002) and Woroch (2002) reveals that, in year 2000, the vast majority of the local network (approximately 94% of total local area revenues totalling $111.8 B at 1999 year end) was operated by incumbent local companies, either independent or part of the Regional Bell Operating Companies (RBOCs) that resulted from the breakup of AT&T in 1984. CLECs captured around 5% of the local area revenues in 2000 with the rest divided among small resellers. The preferred formal process of regulation of state tariffs in year 2000 was price cap.[12] The focus of CLECs on business users preserves the influence of regulators over residential prices as price caps below the monopoly price will be a binding constraint for regulated ILECs with moderate competition.

Another relevant aspect of the TA of 1996 is the redefinition of Universal Service obligations. In the past, regulated firms acted as a monopolists and possessed the ability to keep cross subsidies between customer groups. The TA of 1996 aimed to bring tariffs in line with costs and created explicit universal service subsidies targeted to schools, rural health providers, low income users and high cost areas.[13] State regulators influence the implementation of universal service subsidies trough the designation of eligible carriers to different programs, and choice of price subsidies to low income users. There are currently two programs that reduce the cost of telephone access to low income users: the Lifeline program, which reduces monthly charges, and the Linkup program, which reduces connection charges. The states have the power to increase these subsidies above the basic level set by federal regulators. I describe the Lifeline and Linkup programs fully in Section 3.1.

Current policy debate is concerned with the further regulation of the Internet and improvement of Universal Service with a possible extension of subsidies to Broadband Internet. The Communications Opportunity, Promotion and Enhancement (COPE) Act of 2006 contains specific developments in this area. The TA of 1996 made few provisions on wireless telephony and Internet Access, which have been two areas of growth in the telecommunications sector. If federal and state regulations expand in these segments, the knowledge from the experience of telephone regulation can prove an useful guide for how regulators are likely to structure rates.

[12] Table 1 of Ai and Sappington (2002) provides a summary of the evolution of the modes of regulation in the US. At the end of 1999, 35 states used price caps, 12 states used rate of return, and remaining three states used either rate case moratoria, earnings sharing or deregulated tariffs.

[13] The Universal Service Administrative Company (USAC) is an agency created by the FCC to administer the Universal Service Fund. From 1998 to 2008, the Fund has disbursed approximately $ 57.7 B in different programs. See http://www.usac.org/default.aspx for a detailed breakdown.

3 Data Set

Data on local market characteristics (race groups, income distribution, network size, etc.), state regulators (tariffs, political composition, election rule,etc.) and firm information (costs, quality measures,etc.) is drawn from the United States Census (2000) and reports of the FCC and state regulators. For the most part, this information is obtained from the data set used in Ackerberg et al. (2008).[14] I will make clear below the additional demographic and company information that I add to the data in Ackerberg et al. (2008). The data set covers 7,118 wire center locations in 43 states and the District of Columbia for 8 Regional Bell Operating Companies for the year 2000.

I use the wire center as definition of local market based on the fact that geographic proximity of the households inside one of these areas creates a differentiated community and the economic cost of service is also homogenous inside a wire center. The variation in demand and operational conditions across wire centers contains information that might be masked at the state level , e. g., dispersion in penetration level across the state.

The United States Census (2000) is the source of demand information and it allows me to construct the percentage of total households in a wire center with telephone service, $Tel\ Pen\ Total$. The definitions of local market demographic variables are relegated to Appendix A. Panel (a) of Table 1 provides summary statistics for these demographic variables. Figure 1 contains the maps of telephone penetration for the states of Alabama and New York as an illustration.[15] Sections 3.1. and 3.2. describe the price and cost data.

3.1 Prices and Low-Income Discounts

The information on regulated tariffs was collected directly from the public utility commissions for Ackerberg et al. (2008). The local telephone service is charged according to usage-based, flat or hybrid rate plans. This raw tariff data is used to construct the minimum expense of completing different numbers of local calls per month: no calls (the utility of the telephone line is limited to completing emergency calls), 50, 100 and 200 calls. This allows for the construction of proxies for the cost of access given the level of use: $Monthly\_0$, $Monthly\_50$, $Monthly\_100$ and $Monthly\_200$. The use of price proxies is partly motivated by the absence of detailed usage data, but it seems reasonable

[14] I thank the authors for making this dataset available to me.
[15] The full set of telephone penetration maps is available from the author upon request.

given the prevalence of flat tariffs and inelastic local usage demand. The initial *Connection* charge is included as an additional price control.

Low income consumers can access lower rates through participation in the Lifeline and Linkup programs.[16] The Lifeline program subsidizes the monthly cost of telephone service and depends on the policy of federal and state regulators. The federal regulator provides a basic subsidy equal to the federal subscriber line charge (SLC) plus $ 1.75 for a total of $ 5.25 in year 2000, for all states except District of Columbia which had a lower SLC. The state regulators are free to provide additional support and the federal administration is committed to providing 50 cents of additional support for each dollar of state subsidy up to a determined cap.[17] The Linkup program at the federal level provides a discount equal to the minimum of $ 30 and 50% of the regular price. State regulators are free to provide Linkup support and there is no form of federal matching. The corresponding proxies for subsidized prices are listed as $Monthly\_0(sub)$, $Monthly\_50(sub)$, $Monthly\_100(sub)$, $Monthly\_200(sub)$ and $Connection(with\ subsidy)$.

Additional details on the political profile of regulators, competition and the price setting process are relegated to Appendix A. Panel (b) of Table 1 provides summary statistics of regulator's characteristics, competition and prices.

3.2 Cost and Quality Characteristics

Cost data is required to form a measure of the profits of the regulated firms. The cost data is drawn from the Hybrid Cost Proxy Model (HCPM) employed by the FCC to determine which wire centers are above the national average cost of service. The FCC developed in a series of Orders the Universal Service provisions in the TA of 1996 for high cost areas. The key document for the incumbent ILECs in the sample is the FCC Ninth Report and Order (1999), which sets subsidies for non rural ILECs in states with average costs above the HCPM national cost benchmark.[18] This FCC Order also set transitional subsidies for non rural ILECs that did not qualify under the HCPM criteria but received

[16] Estimates of the participation in Lifeline and Linkup are available at the state level. I employ a filing of National Consumer Law Center (2001) to the FCC to obtain an estimate of the ratio of participants to eligible consumers. This is cross checked with the FCC monitoring report (1999).

[17] The cap on federal lifeline subsidy per line was $ 7 for year 2000. Given a basic federal subsidy of $ 5.25, state regulators can anticipate additional federal funds for state subsidies below $ 3.5.

[18] The state average costs for the non rural ILECs are compared to the national average. For those states exceeding 135% of the national average, the ILEC is eligible to high cost model support. The subsidy at each wire center in that state will equal 76% of the difference between wire center cost per line and the national average. If the subsidy exceeds a cap of state available funds, it will be reduced proportionally in all wire centers. The states affected in the sample include AL, KY, ME, MS and WV.

subsidies under preexisting programs.[19] All companies in the sample qualify as non rural.

The results for the year 2000 are public and allow me to form estimates of average and marginal cost per line. For a given number of target users, the HCPM employs data on the geographic characteristics of wire centers and input prices to calculate the minimum total cost of building and operating the local network. The output of this model is a total cost per wire center that can be used for the average and marginal cost estimation. The HCPM also provides an estimate of the cost of capital of the regulated ILECs: 11.25%. This figure was outdated in year 2000 as it was based on target return levels evaluated by the FCC at the beginning of the 1990s to set price caps. It is possible to use the evolution of corporate bond rates to proxy for the change in the cost of capital and obtain an updated estimate of 8.75 %.[20]

The FCC also maintains the Automated Reported System (ARMIS) to which large exchange carriers are required to report operational and financial data. The FCC 43-05 Service Quality Report and the FCC 43-06 Customer Satisfaction Report allow me to collect the number of *Complaints per* 1000 *lines* (broken down by residential and business customers at the state level) and number of two or more minutes *Downtime* (reported at the wire center level). This information allows me to construct a basic measure of the quality of the operations across the state. Panel (c) of Table 1 provides summary statistics.

4 Model

In this section, I describe the components of the optimal regulation model. In section 4.1., I set up the demand model. The reader exclusively interested in demand can read this subsection and skip ahead to 5.1., 6.1. and 6.2. Section 4.2. constructs the objective function and sets up the maximization problem of the regulator. Sections 4.3. and 4.4. form the necessary first order conditions derived from the optimization problem in 4.2. Section 5.2. ahead adapts the first order conditions to the estimation procedure. The derivations are completed for a given state s so I save the inclusion of subindex s in functions to lighten notation. Henceforth, I will use the term local market rather than wire center.

[19]The hold-harmless provision woul initially keep constant the the total amount of support for non rural ILECs excluded from the high cost model program. The FCC Thirteenth Report and Order (2000) set up the a phase down schedule of this interim program. In the sample, the RBOCs affected are in AR,CO,KY,NM and SC.

[20]The original computation assumes 44% of debt in the capital structure, a cost of debt of 8.8% and cost of equity of 13.2%. The evolution of Moody's Baa Corporate Bonds is used to measure the decrease in the cost of equity from 1991 to 2000. See pp. 74-76 Uri (2004) for a more detailed review of the argument.

4.1 Demand for residential telephone access

I derive the local market demand function by applying a random utility model to the local market level. A state s is divided into Z_s price zones and each price zone contains N_{zs} local markets. A household i in local market $j \in \{1, ..., N_{zs}\}$ at a price zone $z \in \{1, ...Z_s\}$ obtains random utility u_{ijz} from access to the local telephone network. Formally,

$$u_{ijz} = x_j\beta - \widetilde{p}_{zi} \cdot \alpha_i + \xi_j + \epsilon_{ijz} \tag{1}$$

where x_j is a $(1 \times K_1)$ vector of observed local market characteristics affecting the mean value of service (for example, ethnic composition and number of households in the local calling area). Net Prices are listed in the (1×2) vector $\widetilde{p}_{zi} \equiv [\widetilde{p}_{zi}(m),\ \widetilde{p}_{zi}(c)]$, where $\widetilde{p}_{zi}(m)$ is the net monthly fee and $\widetilde{p}_{zi}(c)$ is the net connection charge faced by household i.[21] The subindex i indicates that discounts are a function of the income of household i. The price coefficient are in a (2×1) vector $\alpha_i \equiv\ [\alpha_i(m),\ \alpha_i(c)]^T$ where $\alpha_i(m)$ equals the household i marginal utility of income (MUI) and $\alpha_i(c)$ equals the marginal utility from a connection charge reduction. The connection charge is a one time payment. The intertemporal discount rate of household i will then enter $\alpha_i(c)$ to express the disutility of the connection charge in terms comparable to the monthly fee. I assume α_i to be inversely proportional to household income I_i in an approximation to the specification in BLP(1995):[22]

$$\alpha_i = \frac{\alpha}{I_i}$$

This functional form allows me to test whether price sensitivity is not responsive to income and close to zero ($\alpha \to 0$) or varying with income and different from zero ($\alpha > 0$). The unobserved elements of utility include the mean market quality ξ_j (unobserved to the econometrician but available to the rest of agents) and a purely idiosyncratic shock ϵ_{ijz} with the standard Type-I (Gumbell) extreme value distribution. The distribution of ξ_j is left unspecified. The researcher can only estimate the difference in utility with respect to the outside option, $u_{i,0}$, with the mean component $x_0\beta + \xi_0$ normalized to zero and subject to its own idiosyncratic shock ϵ_{i0} with the logit form. The distributional assumption

[21] Net prices $\widetilde{p}_{zi}$ are calculated as the difference of regular prices p_z and discounts d_{zi} for low income consumers: $\widetilde{p}_{zi} = p_z - d_{zi}$. Note that $p_z \equiv [p_z(m),\ p_z(c)]$ and $d_{zi} \equiv [d_{zi}(m),\ d_{zi}(c)]$.

[22] This formulation is a linear approximation to the logarithmic term $\alpha \cdot [\log(I_i - p_{zi}) - \log(I_i)]$ derived from a Cobb-Douglas utility function in BLP (1995). A $\alpha_i(m)$ linear in demographic characteristics as in Nevo (2001) does not alter significantly the results.

on ϵ_{ijz}, ϵ_{i0} allows me to use the results in Train (2002) Chapter 3 or Small and Rosen (1981) to derive an analytic expression for the probability of telephone adoption of household i at location jz:

$$P_{ijz}(x_j, \widetilde{p}_{zi}, \xi_j, I_i, \Theta_D) = \frac{\exp(x_j\beta - \widetilde{p}_{zi} \cdot \alpha_i + \xi_j)}{1 + \exp(x_j\beta - \widetilde{p}_{zi} \cdot \alpha_i + \xi_j)} \tag{2}$$

where Θ_D condenses the demand side parameters. The expectation of P_{ijz} with respect to household income I_i (both α_i and $\widetilde{p}_{zi}$ are a function of income) yields the proportion of households P_{jz} with local telephone service at location jz. That is,

$$P_{jz}(x_j, \widetilde{p}_z, \xi_j, \Theta_D) = \int P_{ijz}(x_j, \widetilde{p}_{zi}, \xi_j, I_i, \Theta_D) dF_{jz} \tag{3}$$

The demand D_{jz} in market j in zone z is simply the product of P_{jz} and the number of households H_{jz}. I also use the probability of adoption P_{jzg} and the demand D_{jzg} of a specific demographic group g by drawing household income exclusively from this group, i. e. $F_{jz}(I \mid i \in g)$.[23] In particular, I can compute the probability of adoption of households divided in G income levels.

4.2 The regulator

I consider a set of state regulators $s \in \{1, ...S\}$ with jurisdiction over multiple local markets distributed across a set of price zones $\{1, ...Z_s\}$ for each state s. The set of price zones is taken as an exogenous constraint for regulator s. The number of local markets inside a zone z is indexed as $\{1, ..., N_{zs}\}$. The regulatory problem under consideration is the choice in each price zone z of a set of net residential monthly prices $\widetilde{p}_{zg}(m)$ for different groups $g \in \{1, ..., G\}$ of residential users.

I focus on the decision over the monthly charge $\widetilde{p}_{zg}(m)$, which constitutes the main expense associated to local phone service for consumers. Even under the presence of bounded rationality, it is then reasonable to assume that regulators are aware of the trade off between consumer surplus and profits in making this decision. This claim would be harder to sustain for the connection charge $\widetilde{p}_{zg}(c)$ as it represents a very small fraction of the residential telephone expenses and it is plausibly a second order magnitude for the consumers and the regulator. The price $\widetilde{p}_{zg}(c)$ is thus assumed to depend only on exogenous state conditions.[24] I assume an objective function W_s for regulator s that captures the

[23] For example, the demand D_{jz} at location jz with a group 1 and a group 2 can be equivalently recovered as $P_{jz} \cdot H_{jz} = D_{jz}$ or $P_{jz1} \cdot H_{jz1} + P_{jz2} \cdot H_{jz2} = (P_{jz1} \cdot \Pr_{jz}(i \in 1) + P_{jz2} \cdot \Pr_{jz}(i \in 2)) \cdot H_{jz} = P_{jz} \cdot H_{jz} = D_{jz}$. Here, $\Pr_{jz}(i \in g)$ denotes the proportion of the population belonging to group g.

[24] From 4. 1., each $\widetilde{p}_{zg}$ is a (1×2) vector with components $\widetilde{p}_{zg}(m)$ for net monthly price and $\widetilde{p}_{zg}(c)$ for net connection.

discussed trade-off between consumer surplus and profits in the choice of $\widetilde{p}_{zg}(m)$. That is,

$$W_s = E\left[\sum_{z=1}^{Z_s}\left(\sum_{j=1}^{N_{zs}}\sum_{g=1}^{G}\lambda_{zg}\cdot CS_{jzg}(\widetilde{p}_{zg},.)+\pi_{jzg}(\widetilde{p}_{zg},.)\right)\mid \iota_s\right] \tag{4}$$

where π_{jzg} and CS_{jzg} are the profit of the firm and consumer surplus from residential local telephone use of group g in local market j of zone z. The term λ_{zg} is the welfare weight of the regulator on consumers of group g (with respect to the firm) in price zone z. Note that the regulator is maximizing the expected weighted surplus $E[\ .\ \mid \iota_s]$ given the knowledge of her information set ι_s. The next subsections make precise the information about demand and cost conditions contained in ι_s.

This formulation allows for very general price discrimination across demographic groups and geographic regions. In reality, price discrimination across demographic groups is limited to price differences between low income consumers and the general population. This price discrimination takes place through the subsidy programs Lifeline and Linkup. I restrict then the number of groups to $G = 2$ for a subsidy eligible (low income) consumer group and a non-eligible consumer group. Given this degree of flexibility for regulatory pricing, the divergence of prices across regions or customer types might respond to different demand and cost conditions, consistent with optimal Ramsey pricing. However, differences in the term λ_{zg} across g and z (specifically, differences in λ_{zg} away from 1) will induce dispersion in prices that reflects varying degrees of bias towards different consumer groups.

A regulator with bias is still constrained by the need of the firm to break even at the state level. The recovery of a minimum revenue base from the regulated local telephone activity might be required by state statutes and, even if this requirement is lax, the regulator is constrained by the possibility of bankruptcy. The profit constraint of the regulator is then given by:

$$E\left[\sum_{z=1}^{Z_s}\sum_{j=1}^{N_{zs}}\sum_{g=1}^{2}\pi_{jzg}(\widetilde{p}_{zg},.)-B_s\mid \iota_s\right]\geq 0 \tag{5}$$

where B_s is the required profit from local residential phone service in state s. The term B_s reasonably increases in the level of debt of the regulated company and it decreases with the size of the profits from other services offered (business local telephone service, etc.) and profits from other states in which the firm operates. I do not specify this term as it does not play a role in the estimation strategy.

Then, $\widetilde{p}_z = p_z - d_z$ is a $(G\times 2)$ vector with net prices for each group in zone z given by $(\widetilde{p}_{z1,...,}\widetilde{p}_{zG})^T$. Prices for a group are homogenous in a zone so $\widetilde{p}_{jg} = \widetilde{p}_{zg}$ for $j\in\{1,2,...,N_{zs}\}$. In the application below, I set $G = 2$.

4.2.1 Consumer Surplus

The expected total consumer surplus is derived as the expectation household surplus with respect to the joint density of the individual income and idiosyncratic shocks. The regulator is assumed to know the mean market value of phone service at a local market j in zone z given by $\delta_j = x_j\beta + \xi_j$. This is reasonable given the fact that local phone service is a mature sector where regulators are likely to have good information about mean local market conditions but they lack detailed survey data. Formally, consumer surplus at location j in zone z for group g is given by:

$$E\left[CS_{jzg}(x_j, \widetilde{p}_z, \xi_j, \Theta_D) \mid \iota_s\right] = M_{jzg} \cdot \int_{A(I)} \frac{1}{\alpha_i(m)} \int_{A(\epsilon)} (x_j\beta - \widetilde{p}_{zg} \cdot \alpha_i + \xi_j + \epsilon_{ijz})\, dF_{jzg}$$

where notation is expanded with respect to equation (4) to account for dependence on all demand variables and parameters. dF_{jzg} is the density with respect to income and the idiosyncractic shock. That is,

$$dF_{jzg} = f_{jzg}(I) \cdot f(\epsilon) \cdot dI \cdot d\epsilon$$

Independence of individual household characteristics allows me to compute easily consumer surplus as the product of the number of consumers M_{jzg} in a group g and the expected surplus of an individual household i in that group g. The logit form of ϵ_{ijz} also allows to write the above formula for consumer surplus more explicitly as:

$$E\left[CS_{jzg}(x_j, \widetilde{p}_{zg}, \xi_j, \Theta_D) \mid \iota_s\right] = M_{jzg} \cdot \int_{A(I)} \frac{Ln\ \left(1 + \exp(x_j\beta - \widetilde{p}_{zg} \cdot \alpha_i + \xi_j)\right)}{\alpha_i(m)}\ f_{jzg}(I)dI$$

where division by the MUI, $\alpha_i(m)$, reduces the consumer surplus to monetary units comparable with the profit of the firm.[25] Given $G = 2$ consumer groups and N_{zs} local markets inside a price zone, the total consumer surplus in the state is given by:

$$\sum_{z=1}^{Z_s}\sum_{j=1}^{N_{zs}}\sum_{g=1}^{2} \lambda_{zg} \cdot E\left[CS_{jzg}(\widetilde{p}_{zg},\ .) \mid \iota_s\right]$$

where notation for all arguments of consumer surplus except prices $\widetilde{p}_{zg}$ has been dropped.

[25] See Small and Rosen (1981) for the original derivation of the inner integral. This is an approximation to the true expected consumer surplus as MUI is fixed at the level of income without acquisition of local telephone service. McFadden (1999) provides an exact approximation to welfare. This approximation is motivated by the small size of the telephone bill as a portion of total income.

4.2.2 Profit

The expected profit of the firm from residential service offered in local market j in zone z for each group g requires knowledge of the expected demand function D_{jzg}, net monthly prices $\widetilde{p}_{zg}(m)$ and net connection charge $\widetilde{p}_{zg}(c)$, the monthly discount of the firm r_s, expected marginal monthly cost per line mc_{jz} and the expected fixed cost F_{jz} per month. The connection charge $\widetilde{p}_{zg}(c)$ is a one time revenue and I use the discount rate r_s to compute a monthly payment comparable to the monthly fee $\widetilde{p}_{zg}(m)$.[26] The regulator is assumed to know the expected rate of adoption P_{jzg} from (3). Expected demand D_{jzg} is then derived from the product of the number of households H_{jzg} and this rate P_{jzg}.

The profit function (and the first order conditions with respect to prices in sections 4.3. and 4.4.) are linear in marginal cost. It is then possible to integrate with respect to the distribution of cost and input the regulator's best estimate for marginal cost $E\left[mc_{jz} \mid \iota_s\right]$ in these expressions. I can then write expected monthly profits at jz from g as:

$$E\left[\pi_{jzg}(p_{zg}, d_{zg}) \mid \iota_s\right] = \left(\widetilde{p}_{zg}(m) + \widetilde{p}_{zg}(c) \cdot r_s - E\left[mc_{jz} \mid \iota_s\right]\right) \cdot D_{jzg} - (1/G) \cdot E\left[F_{jz} \mid \iota_s\right]$$

The profit of the firm operating in state s results from the sum of revenues and costs across the different price zones $\{1, 2, ..., Z_s\}$ and the local markets inside each zone:

$$E\left[\pi_s(p_{11}, d_{12}, ..., p_{Z_s 1}, d_{Z_s 2}) \mid \iota_s\right] = \sum_{z=1}^{Z_s} \sum_{j=1}^{N_{zs}} \sum_{g=1}^{2} E\left[\pi_{jzg}(p_{zg}, d_{zg}) \mid \iota_s\right]$$

This form of expected profits measures total industry profits at regulated prices, as it is based on total demand function D_{jzg} from every group g at each local market jz. This expression neglects competition on the basis of the relatively small share of CLECs (see data section 3.1. and Appendix A). Furthermore, existing empirical evidence such as Economides et al. (2008) reveals that the entry of competition in local residential telephony does not lead to big changes in the price level. This fact provides additional justification for using regulated prices to calculate total residential profits.

The use of net prices $\widetilde{p}_{zg}$ in the above profit formula assumes full internalization of the cost of price discount programs by state regulators. However, the discounts are not entirely funded from state sources but also disbursements from the federal Universal Service Fund (USF). State regulators might

[26] The adjusted monthly connection charge is simply given by $\widetilde{p}_{zg}(c) \cdot r_s$. This form of firm revenues neglects the fact that $\widetilde{p}_{zg}(c)$ represents a sunk cost for a majority of consumers but it is a good aproximation as long as regulated monthly prices are not set high enough that a substantial fraction of the installed base decides to drop local telephone service.

still weigh the costs of USF funds if higher future contributions to USF, or increased administrative costs are associated to a greater current use of the USF. I can not infer the importance of these factors from the data, so I formulate in the next subsection an alternative model with partial state internalization of subsidy costs and I estimate both models.

The regulator's best estimate of marginal cost is assumed linear in a set cost shifters $E\left[mc_{jz} \mid \iota_s\right] = \gamma \cdot Cost_{jz}$. This is formally equivalent to the marginal cost being linear in cost shifters $Cost_{jz}$ and a mean independent shock ω_{jz}:[27]

$$mc_{jz} = \gamma \cdot Cost_{jz} + \omega_{jz} \tag{6}$$

The error ω_{jz} reflects the imperfect knowledge of mc_{jz} by the regulator, who is limited to use the best estimate $E\left[mc_{jz} \mid \iota_s\right]$ in the calculation of expected welfare. For estimation, I also introduce a more limited specification that assumes constant expected marginal cost inside a price zone z and reflects a coarser knowledge of costs by the regulator:

$$mc_{_{jz}} = \gamma \cdot Cost_z + \omega_{jz} \tag{7}$$

4.2.3 Regulatory Bias

The weight λ_{zg} that the regulator places in the consumer surplus of group g in zone z is assumed to depend on the political characteristics of the regulator and demographic characteristics of the constituency inside the price zone z. This set of variables is summarized as Pol_{zg}. As an example, the availability of affordable telephone service in rural areas might a priori yield higher political benefits and regulators will put more weight on the consumer surplus in these areas. The following functional form is adopted:

$$\log\left(\lambda_{zg}\right) = \phi \cdot Pol_{zg} + \eta_{zg} \tag{8}$$

where ϕ is a vector of parameters and η_{zg} is a mean independent shock. I denote the parameters (ϕ, γ) jointly as Θ_s capturing the impact of cost and policy shifters. The regulator knows her own preferences so λ_{zg} rather than $E\left[\lambda_{zg} \mid \iota_s\right]$ is used to compute W_s. Again, I introduce an alternative

[27] It is possible to impose an analogous structure into $E[F_{jz} \mid \iota_s]$.but this is not relevant for estimation as I do not recover information on the fixed costs.

simplified specification that considers a common weight in zone z:

$$\log(\lambda_z) = \phi \cdot Pol_z + \eta_z \tag{9}$$

4.3 Local Tariff Choice

Given the assumptions in the model,[28] the choice of the net monthly fee $\widetilde{p}^*_{zg}(m)$ for each price zone z and group g satisfies the following first order condition:

$$\frac{\partial W_s}{\partial \widetilde{p}^*_{zg}(m)} = E\left[\sum_{j=1}^{N_{zs}} \frac{\partial CS_{jzg}(.)}{\partial \widetilde{p}^*_{zg}(m)} \cdot \frac{\lambda_{zg}}{1+\mu_s} + \sum_{j=1}^{N_{zs}} \frac{\partial \pi_{jzg}(.)}{\partial \widetilde{p}^*_{zg}(m)} \mid \iota_s\right] = 0$$

where μ_s denotes the Lagrangian multiplier on the budget constraint restriction at the state level in equation (5). A more useful representation of the problem given $G = 2$ considers the choice for each zone z of a general rate $p_z(m)$ and a discount $d_z(m)$. The net prices are then recovered as $\widetilde{p}_{z1}(m) = p_z(m)$ and $\widetilde{p}_{z2}(m) = p_z(m) - d_z(m)$, where $g = 2$ is the low income group. The problem can then be represented by the following pair of first order conditions in each zone z:

$$\frac{\partial W_s}{\partial p^*_z(m)} = E\left[\sum_{j=1}^{N_{zs}} \sum_{g=1}^{2} \left(\frac{\partial CS_{jzg}(.)}{\partial p^*_z(m)} \cdot \frac{\lambda_{zg}}{1+\mu_s} + \frac{\partial \pi_{jzg}(.)}{\partial p^*_z(m)}\right) \mid \iota_s\right] = 0 \tag{10}$$

$$\frac{\partial W_s}{\partial d^*_z(m)} = E\left[\sum_{j=1}^{N_{zs}} \frac{\partial CS_{jz2}(.)}{\partial d^*_z(m)} \cdot \frac{\lambda_{z2}}{1+\mu_s} + \frac{\partial \pi_{jz2}(.)}{\partial d^*_z(m)} \mid \iota_s\right] = 0 \tag{11}$$

I will use equations (10) and (11) as reference for the estimation section below. It is immediate to rewrite these first order conditions as a function of demand and cost factors expected by the regulator according to the information in ι_s. The expansion of (10) and (11) with the best estimate of costs as in (6) would yield:

$$\sum_{j=1}^{N_{zs}} \sum_{g=1}^{2} \left[-D_{jzg} \cdot \frac{\lambda_{zg}}{1+\mu_s} + D_{jzg} + \frac{\partial D_{jzg}}{\partial d^*_z(m)} \cdot \left(\widetilde{p}^*_{zg}(m) + \widetilde{p}^*_{zg}(c) \cdot r_s - \gamma \cdot Cost_{jz}\right)\right] = 0$$

$$\sum_{j=1}^{N_{zs}} \left[D_{jz2} \cdot \frac{\lambda_{z2}}{1+\mu_s} - D_{jz2} + \frac{\partial D_{jz2}}{\partial d^*_z(m)} \cdot \left(\widetilde{p}^*_{z2}(m) + \widetilde{p}^*_{z2}(c) \cdot r_s - \gamma \cdot Cost_{jz}\right)\right] = 0$$

[28] The demand and profit specification ensures that $W_s(.)$ and $\pi_s(.)$ are C^1 functions, which is a key requirement to appy LagrangeTheorem. See Theorem 6.1 in Sudaram (1996) for a formal presentation.

The presence of the regulator implies that the price choice is potentially responsive not only to profit variation but also the impact on consumer surplus. A local monopolist in local market jz would simply maximize expected profits given her information set ι_f, yielding a different first order condition:

$$\frac{\partial \pi_{jzg}(.)}{\partial \widetilde{p}^{*}_{zg}(m)} = E\left[D_{jzg} + \frac{\partial D_{jzg}}{\partial \widetilde{p}^{*}_{zg}(m)} \cdot \left(\widetilde{p}^{*}_{zg}(m) + \widetilde{p}^{*}_{zg}(c) \cdot r_s - mc_{jz}\right) \mid \iota_f\right] = 0$$

4.4 Interaction between State and Federal Regulators

The decisions of the state regulator can be influenced by the presence of federal subsidy programs. In particular, the regulator can orient the pricing of local telephone services to increase the transfers from the federal Lifeline and High Cost Model programs described in section 3. I incorporate the participation into the federal Lifeline program by redefining the profit in local market jz from the eligible consumer group, $g = 2$, as:

$$\pi_{jz2}(p_z, d_z) = (p_z(m) + \widetilde{p}_{z2}(c) \cdot r_s - mc_{jz}) \cdot D_{jz2} - L(d_z(m) \cdot D_{jz2}) \tag{12}$$

where $L(x)$ is C^1. In the standard scenario $L(x) = x$ so the money costs of the subsidy are fully internalized. A general form for $L(x)$ allows me to accommodate the possibility that the cost of an amount of subsidy x is greater or lower than x. This divergence between the state cost and the actual amount of subsidy can be due to the presence of the federal Lifeline program or administrative transaction costs.

The participation in the high cost program adds an extra correction for profits of a state s with a regulated non rural ILEC. These states will receive a subsidy per telephone line equal to 76% of the excess of the average cost per line over the national benchmark. Formally, the high cost model subsidy of state s is given by:

$$HCS_s = \left(\sum_{z=1}^{Z_s}\sum_{j=1}^{N_{zs}} l_{jz} + l_s\right) \cdot 0.76 \cdot \max\left(\frac{\left[\sum_{z=1}^{Z_s}\sum_{j=1}^{N_{zs}} TC_{jz} + TC_s\right]}{\left[\sum_{z=1}^{Z_s}\sum_{j=1}^{N_{zs}} l_{jz} + l_s\right]} - nb, 0\right)$$

where l_{jz} (TC_{jz}) denote the number of residential lines (total cost) of the regulated firm in local market jz and l_s (TC_s) denote all other telephone lines (total cost) in state s. The nb term denotes the national benchmark monthly cost per line ($23.35). For an eligible state, this implies a correction to the marginal profit $\partial\pi_{jzg}(.)/\partial\widetilde{p}^{*}_{zg}(m)$ for local market jz and group g equal to:

$$\frac{\partial HCS_s}{\partial\widetilde{p}^{*}_{zg}(m)} = 0.76 \cdot (mc_{jz} - nb) \cdot \frac{\partial D_{jzg}}{\partial\widetilde{p}^{*}_{zg}(m)} \tag{13}$$

where all terms have been already defined. When a state regulator increases price, this leads to a decrease in residential lines ($\partial D_{jzg} < 0$) with two opposite effects on the amount of high cost funds received. Under mild economies of scale in the number of lines l_{jz}, the cost per line and the corresponding federal subsidy increase. On the other hand, the number of lines over which the subsidy is received is smaller. Given the formula for HCS_s, this implies that increasing the number of lines in local markets below (above) the national benchmark cost per line reduces (increases) the total high cost contribution to the state.

The states in the hold-harmless program must be handled differently. In year 2000, the hold-harmless contribution to state s was fixed at historical level HHC_s but the phase down clauses of this program entailed that the contribution in a subsequent year t would be given by:

$$HHC_s(t) = \left(\sum_{z=1}^{Z_s}\sum_{j=1}^{N_{zs}} l_{jz} + l_s\right) \cdot \max\left(\frac{HHC_s}{\left[\sum_{z=1}^{Z_s}\sum_{j=1}^{N_{zs}} l_{jz} + l_s\right]} - t,\ 0\right)$$

The term $-t$ implies that the hold-harmless support per line is reduced every year. I define T_s as the last year in which a state s receives a hold-harmless contribution and assume that state regulators do not induce demand variations big enough to alter this temporal threshold. The correction to the marginal profit $\partial\pi_{jzg}(.)/\partial\widetilde{p}^{*}_{zg}(m)$ for local market jz and group g in state s is then given by:

$$\sum_{t=1}^{T_s}\frac{\partial HHC_s(t)}{\partial\widetilde{p}^{*}_{zg}(m)} = \sum_{t=1}^{T_s} -\frac{r_s}{(1+r_s)^t} \cdot t \cdot \frac{\partial D_{jzg}}{\partial\widetilde{p}^{*}_{zg}(m)}$$

where the term $r_s/\left(1+r_s\right)^t$ converts the temporal effect of the hold-harmless provision into a monthly perpetuity.

5 Estimation

The approach employed to identify and estimate the parameters of the model (α, β, γ, ϕ) relies on the orthogonality of unobserved demand and supply shocks (ξ, ω, η) to exogenous geographic, demographic and political factors. Given demand side instruments (W), cost shifters ($Cost$) and policy shifters (Pol), the set of orthogonality conditions $E[\xi \cdot W] = 0$, $E[\omega \cdot Cost] = 0$ and $E[\eta \cdot Pol] = 0$ can be used to derive GMM estimators of the parameters.

The GMM estimates of the parameters of the model minimize a function of the sample analogs of the above orthogonality conditions. This setting follows the empirical strategy introduced by BLP (1995) and popularized in the empirical IO literature by Nevo (2000, 2001). See Hansen (1982) and Newey and McFadden (1994) for the original derivation and details on the GMM framework.

The GMM method has the advantage of not requiring a full distributional assumption on the unobserved components of the model. I only need the adequate choice of orthogonality conditions as moments for estimation.[29] Inference will require additional assumptions on the covariance between these moments. In section 5.4., I derive standard errors for the parameters of the model under the assumption of no correlation between the three groups of moments: $E[\xi \cdot W]$, $E[\omega \cdot Cost]$ and $E[\eta \cdot Pol]$. This choice follows from the assumption of a well specified model in which the observed exogenous variables capture the common factors affecting demand, cost and policy moments.

The methodology is detailed next with the main steps including (i) recovery of (ξ, ω, η) (ii) choice of instruments and (iii) details on inference.

5.1 Recovering the shock on demand

I define $n \in \{1, ..., N\}$ as an index over the total number of local market observations, which equals $N = \sum_{s=1}^{S} \sum_{z=1}^{Z_s} N_{zs}$. I estimate the telephone penetration implied by the model in (3) with the simulation of a sample of $H = 100$ households for each local market n. The expectation in (3) lacks an analytical form but it can be simulated from knowledge of the individual household income distribution $F_n(I)$ at local market n. The empirical distribution of household income $\widetilde{F}_n(I)$[30] from the US Census (2000) is used to generate the simulated income samples.[31] Given $(\widetilde{I}_i)_{i=1}^{H}$, it is possible to generate a sample

[29] The exogenous variables must be (i) truly uncorrelated with the errors, and (ii) sufficiently correlated with the jacobian of the errors with respect to the model parameters, or estimation is impossible. Wooldridge (2002) Chapter 14 provides a precise account of the GMM requisites.

[30] I actually draw from $\widetilde{F}_n(\widetilde{D}_i, \widetilde{I}_i)$ where $\widetilde{D}_i$ includes the race $\{black_i, asian_i, native_i, other_i\}$ and the level of income $\widetilde{I}_i$ of each household i. Preliminary estimates of the interaction of race with local market characteristics were very imprecise so I do not pursue this possibility here.

[31] The US Census (2000) reports income into 16 brackets. Given 5 race classes, the joint empirical distribution of income and race consists of the frequencies of 80 excluding classes $\{d_{1,...,}d_{c,...,}d_{80}\}$. Each class is assigned a portion $\{s_{1,...,}s_{c,...,}s_{80}\}$ of the $[0, 1]$ segment according to its frequency. Each simulated household i is obtained by taking a random draw $\widetilde{u}_i$ from $U[0, 1]$ and assigning i to the class d_c for which $\widetilde{u}_i \in s_c$. Income I_i is assigned by taking a uniform draw from $U[l_c, h_c]$, which are the bracket limits for the class c.

$(\widetilde{\alpha}_i, \widetilde{p}_{in})_{i=1}^{H}$ of individual household price coefficients and net prices given the specification in 4.1. Assuming knowledge of (x_n, ξ_n, Θ_D), I can obtain the following simulated analog of (3):

$$\widetilde{P}_n(x_n, \widetilde{p}_n, \xi_n, \Theta_D) = \frac{1}{H} \cdot \sum_{i=1}^{H} P_{in}(x_n, \widetilde{p}_{in}, \xi_n, \widetilde{\alpha}_i, \Theta_D)$$

The estimation algorithm considered in BLP(1995) computes next the mean market value $\delta_n = x_n\beta + \xi_n$ with the equality of the simulated model penetration $\widetilde{P}_n$ with the actual penetration level s_n. This equality is derived by application of the law of large numbers. The estimate of $\widehat{\delta}_n$ makes immediate to extract $\widehat{\xi}_n = \widehat{\delta}_n - x_n\beta$. The demand specification in section 4.1. satisfies the regularity conditions used in BLP(1995) for the equality $\widetilde{P}_n(\delta_n, .) = s_n$ to form a contraction mapping that allows to solve for the estimated $\widehat{\delta}_n$ by iteration steps of the form:

$$\delta_n^{it+1} = \log(s_n) - \log\left(\widetilde{P}_n(\delta_n^{it}, .)\right) + \delta_n^{it} \tag{14}$$

This procedure cannot use observations with $s_n = 1$ as the infinite support of ϵ_{in} excludes $\widetilde{P}_{in}(.) = 1$, and (14) neglects that $\widetilde{P}_n(\delta_n, .) \neq s_n$ for finite number of households H. I am forced to discard 264 observations (3.7% of sample). The possible selection problem is limited given the low percentage of observations discarded and the small differences in penetration between the full and selected sample shown in Table 1.

Telephone penetration levels are much higher than common market shares of differentiated products in an oligopolistic market. The number of iterations for convergence of (14) increases very fast as s_n approaches 1 making the typical implementation of this algorithm in Nevo (2001) unusable.[32] The key problem with the typical implementation is that (14) is applied to the full set of N local markets as long as δ does not converge for at least one market. Given 6854 local markets in the sample, each step of (14) is computationally costly. I find that stopping the iteration for local markets as they achieve convergence solves this computational difficulty. See appendix B for the implementation.

[32] For the available data, the typical demand specification in section 6 and parameter values close to the truth, 700 iterations are required for convergence if $s_n \leq 0.95$. For $0.95 \leq s_n \leq 0.99$, this number climbs to 1750. For $0.99 \leq s_n$, this number exceeds 4500.

5.2 Recovering the shock on the regulator's weights

The first order conditions in (10) and (11) in section 4.3. are the base to form the sample analogs of $E[\eta \cdot Pol] = 0$. The estimation approach used searches for the unobserved weights λ that satisfy (10) and (11) and make prices at least locally optimal. The error η is then recovered by applying on λ the structure in either equation (8) or (9). In subsection 5.2.1., I also use the first order conditions to recover the unobserved marginal cost mc in addition to λ. The error ω is then recovered by applying equation (7). In subsections 5.2.2. and 5.2.3., mc is estimated from the HCPM cost data and the first order conditions (10) and (11) are only used to recover λ.

5.2.1 Price Zone Level mc and λ

For each zone z, I consider first the assumption of a common expected marginal cost $E[mc_{jz} \mid \iota_s] = mc_z = \gamma \cdot Cost_z + \omega_z$ as in (7) and a common weight λ_z across the groups ($\lambda_{z1} = \lambda_{z2} = \lambda_z$) as in (9). This specification assumes a regulator with a relatively coarse knowledge of her jurisdiction as it has no information of cost variation within a zone. It has the advantage of not requiring the use of additional cost data as marginal cost is inferred from first order conditions on prices and it also allows for zone level unobserved error ω_z on the regulator's expected marginal cost. I can then write (10) and (11) as:

$$\frac{\lambda_z}{1+\mu_s} \cdot \partial CS_{zp} + \partial R^o_{zp} - mc_z \cdot \partial D^o_{zp} = 0 \tag{15}$$

$$\frac{\lambda_z}{1+\mu_s} \cdot \partial CS_{zd} + \partial R^o_{zd} - mc_z \cdot \partial D^o_{zd} = 0 \tag{16}$$

where the following abbreviations have been employed:

$$\partial D^o_{zp} = \sum_{j=1}^{N_{zs}} \sum_{g=1}^{2} \frac{\partial D_{jzg}}{\partial p^*_z(m)} \qquad \partial D^o_{zd} = \sum_{j=1}^{N_{zs}} \frac{\partial D_{jz2}}{\partial d^*_z(m)}$$

$$\partial R^o_{zp} = \sum_{j=1}^{N_{zs}} \sum_{g=1}^{2} D_{jzg} + \frac{\partial D_{jz1}}{\partial p^*_z(m)} \cdot \left(\widetilde{p}^*_{zg}(m) + \widetilde{p}^*_{zg}(c) \cdot r_s\right)$$

$$\partial R^o_{zd} = \sum_{j=1}^{N_{zs}} - D_{jz2} + \frac{\partial D_{jz2}}{\partial d^*_z(m)} \cdot (\widetilde{p}^*_{z2}(m) + \widetilde{p}^*_{z2}(c) \cdot r_s)$$

$$\partial CS_{zp} = \sum_{j=1}^{N_{zs}} \sum_{g=1}^{2} \frac{\partial CS_{jzg}(.)}{\partial p^*_z(m)} \qquad \partial CS_{zd} = \sum_{j=1}^{N_{zs}} \frac{\partial CS_{jz2}(.)}{\partial d^*_z(m)}$$

I can rearrange the conditions in (15) and (16) to solve for mc_z and $\lambda_z/(1+\mu_s)$. The subtraction of (15) times $\partial CS_{zd}/\partial CS_{zp}$ from (16) yields mc_z. Formally,

$$mc_z = \frac{\partial R^o_{zd} - \frac{\partial CS_{zd}}{\partial CS_{zp}} \cdot \partial R^o_{zp}}{\partial D^o_{zd} - \frac{\partial CS_{zd}}{\partial CS_{zp}} \cdot \partial D^o_{zp}} \tag{17}$$

Given mc_z, it is immediate to derive $\omega_z = mc_z - \gamma_z \cdot Cost_z$ and it is also possible to obtain $\lambda_z/(1+\mu_s)$ from the substitution of mc_z into (15). After some simplifications, I derive:

$$\frac{\lambda_z}{1+\mu_s} = \frac{\partial R^o_{zd} \cdot \partial D^o_{zp} - \partial R^o_{zp} \cdot \partial D^o_{zd}}{\partial CS^o_{zp} \cdot \partial D^o_{zd} - \partial CS^o_{zd} \cdot \partial D^o_{zp}} \tag{18}$$

It is possible to eliminate the Lagrangian multiplier μ_s by using differences of the expression in (18) across consumer groups in different zones. Alternatively, it is possible to avoid the bias from the omission of μ_s by the inclusion of suitable state fixed effects, and I focus the exposition on this latter approach. In the sample, I will employ the index $d \in \{1, ..., D\}$ over the set of all welfare weights with $D = \sum_{s=1}^{S} Z_s$ (number of zones). For marginal costs, I will employ the index $p \in \{1, ..., P\}$ where $P = \sum_{s=1}^{S} Z_s$.[33] The set of available welfare weights and costs are collected as $\{\lambda_1, ..., \lambda_D\}$ and $\{mc_1, ..., mc_P\}$. I then take the following marginal cost and weight equations to the data:

$$mc_p = \gamma \cdot Cost_p + \omega_p \tag{19}$$

$$\log(\lambda_d) - \log(1+\mu_s) = \sum_{s=2}^{S} \phi_s \cdot 1_{ds} + \phi \cdot Pol\_S_d + \eta_d \tag{20}$$

where the observations for λ and mc are computed from (17) and (18). The state fixed effects ϕ_s control for the effect of $-\log(1+\mu_s)$ and any other possible state-level unobserved heterogeneity. These fixed effects are estimated by including the $(1 \times (S-1))$ vector of state dummy variables 1_{ds}. The set of policy shifters Pol_d combines then fixed effects (1_{ds}) and all other policy variables (Pol_S_d).

5.2.2 Local Market Level mc and Group-Zone Level λ

I consider that state regulators use a best estimate of marginal cost $E[mc_{jz} \mid \iota_s] = \gamma \cdot Cost_{jz}$ as in (6) and a different λ_{zg} for each zone z and group g as in (8). Given an estimate $\widehat{mc}_{jz}$ of $E[mc_{jz} \mid \iota_s]$, it is

[33] In this case, the number of weight and cost observations coincides ($D = P = \sum_{s=1}^{S} Z_s$). This is not the case in all the specifications so I introduce the two different indexes p and d.

then possible to write $\partial\pi_{jzg}(.)/\partial p_z^*(m)$ and $\partial\pi_{jz2}(.)/\partial d_z^*(m)$ in the first order conditions in (10) and (11) as:

$$E\left[\frac{\partial\pi_{jzg}(.)}{\partial p_z^*(m)} \mid \iota_s\right] = \frac{\partial D_{jzg}}{\partial p_z^*(m)} \cdot \left(\widetilde{p}_{zg}^*(m) + \widetilde{p}_{zg}^*(c) \cdot r_s - \widehat{mc}_{jz}\right) + D_{jzg} \tag{21}$$

$$E\left[\frac{\partial\pi_{jz2}(.)}{\partial d_z^*(m)} \mid \iota_s\right] = \frac{\partial D_{jz2}}{\partial d_z^*(m)} \cdot \left(\widetilde{p}_{z2}^*(m) + \widetilde{p}_{z2}^*(c) \cdot r_s - \widehat{mc}_{jz}\right) - D_{jz2} \tag{22}$$

For a given z and g, it is immediate to obtain from (10) and (11) that:

$$\frac{\lambda_{z1}}{1+\mu_s} = E\left[-\sum_{j=1}^{N_{zs}} \frac{\partial\pi_{jz1}(.)}{\partial p_z^*(m)} \Big/ \sum_{j=1}^{N_{zs}} \frac{\partial CS_{jz1}(.)}{\partial p_z^*(m)} \mid \iota_s\right] \tag{23}$$

$$\frac{\lambda_{z2}}{1+\mu_s} = E\left[-\sum_{j=1}^{N_{zs}} \frac{\partial\pi_{jz2}(.)}{\partial d_z^*(m)} \Big/ \sum_{j=1}^{N_{zs}} \frac{\partial CS_{jz2}(.)}{\partial d_z^*(m)} \mid \iota_s\right]$$

If I substitute for the profit and consumer surplus derivatives in (23), I can derive a simplified expression,

$$\frac{\lambda_{z1}}{1+\mu_s} = 1 + \left[\sum_{j=1}^{N_{zs}} \frac{\partial D_{jzg}}{\partial p_z^*(m)} \cdot \left(\widetilde{p}_{zg}^*(m) + \widetilde{p}_{zg}^*(c) \cdot r_s - \widehat{mc}_{jz}\right)\right] \cdot \frac{1}{\sum_{j=1}^{N_{zs}} D_{jzg}}$$

that shows how the presence of positive (negative) markups over cost measure $\widehat{mc}_{jz}$ decreases (increases) the estimated weight, and they do more so the higher the absolute value of $\partial D_{jzg}/\partial p_z^*(m)$. Note again that the presence of the Lagrangian multiplier μ_s prevents the immediate recovery of λ_{zg}. However, I could take the expression in (23) for zone 1 and group 1 as a base to obtain for each group g and zone z the ratio:[34]

$$\lambda_{zg}^* = \frac{\lambda_{zg}}{\lambda_{11}} = \frac{E\left[\sum_{j=1}^{N_{zs}} \frac{\partial\pi_{jzg}(.)}{\partial p_z^*(m)} \Big/ \sum_{j=1}^{N_{zs}} \frac{\partial CS_{jzg}(.)}{\partial p_z^*(m)} \mid \iota_s\right]}{E\left[\sum_{j=1}^{N_{1s}} \frac{\partial\pi_{j11}(.)}{\partial p_1^*(m)} \Big/ \sum_{j=1}^{N_{1s}} \frac{\partial CS_{j11}(.)}{\partial p_1^*(m)} \mid \iota_s\right]} \tag{24}$$

For example, a state with two zones will yield four ratios $\lambda_{11}^* = \lambda_{11}/\lambda_{11} = 1$, $\lambda_{12}^* = \lambda_{12}/\lambda_{11}$, $\lambda_{21}^* = \lambda_{21}/\lambda_{11}$ and $\lambda_{22}^* = \lambda_{22}/\lambda_{11}$. Again, an alternative approach would add to Pol_d the state dummies in 1_{ds}. The index $d \in \{1, ..., D\}$ over the set of all available welfare weights in the data is now

[34] The ratio in (24) assumes a group g that is not eligible so the derivatives $\partial\pi_{jzg}(.)/\partial p_{zg}^*(m)$ and $\partial CS_{jzg}(.)/\partial p_z^*(m)$ are used. If the group is eligible, I use derivatives with respect to d_z^*.

defined by $D = \sum_{s=1}^{S} 2 \cdot Z_s$ (twice the number of zones). I can take now the welfare weight equation to the data:

$$\log(\lambda_d) - \log(1 + \mu_s) = \sum_{s=2}^{S} \phi_s \cdot 1_{ds} + \phi \cdot Pol\_S_d + \eta_d$$

In order to estimate the cost parameters for this specification and obtain $\widehat{mc}_{jz}$ for each local market jz, I make use of the availability of additional cost data from the HCPM. The total cost estimate in the HCPM, TC_{HCPM}, can be used as a proxy for the true total cost. In the sample, I have an observation of TC_{HCPM} for each local market. It is then possible to estimate a general equation:

$$TC_{HCPM}{}_{,p} = g\left(Cost_p, \gamma\right) + \omega_p \tag{25}$$

where $g(.,.)$ is a C^1 function of cost shifters $Cost_p$ and parameters γ. In the application in section 6, I use a simple specification of $g(.,.)$ linear in γ as in Rosston et al.(2008). For consistency with subsection 5.2.1., I use the index p for cost observations. Note however that for this specification the set of cost observations $p \in \{1, ..., P\}$ coincides with the set of all available local markets $n \in \{1, ..., N\}$. If I take the number of target residential lines in the HCPM, $reslines$, as belonging to the set of cost shifters, the estimate of marginal cost is derived as:

$$\widehat{mc}_p = \partial g\left(Cost_p, \hat{\gamma}\right) / \partial reslines$$

Given a specification of $g(.,.)$ linear in γ, I can obtain $\widehat{mc}_p = \widehat{\gamma} \cdot Cost\_mc_p$, where $Cost\_mc_p \subseteq Cost_p$, as not all the cost shifters affecting TC_{HCPM} necessarily enter into $\widehat{mc}_p$. Note that the use of the HCPM model adds additional information to the estimation as it is now possible to compute expected marginal cost for each local market rather than for each zone.

5.2.3 Local Market Level mc, Group-Zone Level λ and Federal Interaction

I modify the specification in 5.2.2. to account for the state incentives to obtain federal subsidies considered in section 4.4. The monetary cost of low income subsidies is modelled with the function $L(x)$. I do not estimate the exact functional form of $L(x)$ or $\partial L(x)/\partial x$ as I lack suitable information on the state administrative costs of the Lifeline program. I rather use several informed specifications of $L(x)$ that incorporate the state effects of the federal Lifeline program. Formally, the specification *Federal I* appends at a local market jz with a discount $d_z(m) \leq \$10.5$ the following correction to $\partial\pi_{jz2}(.)/\partial d_z(m)$:

$$\frac{\partial L(\ d_z(m) \cdot D_{jz2}\ )}{\partial d_z(m)} = \frac{2}{3} \cdot \ \left[(d_z(m) - 5.25) \cdot \frac{\partial D_{jz2}}{\partial d_z(m)} + D_{jz2}\right] \tag{26}$$

The term in (26) is the marginal state cost at local market jz of increasing the discount $d_z(m)$ (Lifeline subsidy). This derivative captures the federal matching of state Lifeline contributions described in section 3.1. The key effect of federal matching is the reduction of marginal state cost of the subsidy to 2/3 of the marginal increase in total subsidy dollars. This applies as long as the discount does not exceed \$10.5. I use a different correction at local markets with $d_z(m) > \$10.5$:

$$\frac{\partial L(\ d_z(m) \cdot D_{jz2}\ )}{\partial d_z(m)} = \left[\frac{2}{3} \cdot (10.5 - 5.25) + (d_z(m) - 10.5)\right] \cdot \frac{\partial D_{jz2}}{\partial d_z(m)} + D_{jz2} \tag{27}$$

This is motivated by the fact that the 2/3 discount is not applied to the portion of the subsidy above the matching region: $(d_z(m) - 10.5)$.[35] This formulation imposes a marginal cost of Lifeline subsidies as in (26) for all states except Massachusetts, Maryland and Rhode Island, which have Lifeline subsidies significantly above the matching region. In *Federal I*, states at the margin (a subsidy level at the minimum $d_z(m) = 5.25$ or at $d_z(m) = 10.5$) are assigned the marginal state cost at (26). This assumes that states at the margin can obtain additional federal matching funds by increasing state subsidies marginally. This is a particular assumption for which the data set does not provide guidance so I check the robustness of the results with an alternative specification: *Federal II*.

Federal II reduces the incentives to obtain federal transfers for states at the margin. States with a contribution $d_z(m) = 10.5$ are assumed now to have a higher marginal state cost of Lifeline subsidy equal to (27) rather than (26). States with a contribution equal to the minimum $d_z(m) = 5.25$ are also assigned the full marginal cost of the subsidy, which is given in this case by:

$$\frac{\partial L(\ d_z(m) \cdot D_{jz2}\ )}{\partial d_z(m)} = (d_z(m) - 5.25) \cdot \frac{\partial D_{jz2}}{\partial d_z(m)} + D_{jz2}$$

This new specification leaves 17 states affected on the margin by the federal Lifeline matching.

[35] Given the scheme described in section 3.2, the total state Lifeline subsidy d_{sz} for a choice of total subsidy d_z in $[\$5.25, \$10.5]$ is given by $d_{sz} + 0.5 \cdot d_{sz} = d_z - \$5.25 \rightarrow d_{sz} = (2/3) \cdot (d_z - \$5.25)$.

The assumptions in *Federal II* imply that the federal matching contributions do not change for small deviations around \$0 or \$3.5. This can be justified if the administrative costs around these subsidy levels absorb the benefit of federal matching.

The correction for the high cost program participation described in 3.2. and 4.4. is straightforward. I append the expression in (13) to the marginal profit in (21) and (22) for the participating states. There is no need to adjust the profits of states receiving hold-harmless contributions since these subsidies were not received after year 2000 for the hold-harmless firms in the sample (AR, CO, KY, NM, SC).

5.3 Identification

This section outlines how the different data sources are used to identify and estimate the different parameters. I refer the reader to Section 3 and Appendix A for the description of the data set.

The variation in the cross section of demographics (ethnic groups, total number of households, etc.) identifies demand parameters in β. As for the price coefficients α, I rely on price and income distribution variation across local markets. For local markets with comparable prices and demographics (excluding income), the difference in the distribution of income contributes to explain differences in penetration levels. Prices $\widetilde{p}^*_{zg}(m)$ are not exogenous but endogenously chosen by the regulator so it is necessary to find suitable instruments for estimation. I do not search for an optimal set of instruments as in BLP(1995),[36] but I limit the analysis to a set of instruments informed by the regulatory problem. I use the constrained optimization problem of the regulator as a basis to find instruments that are correlated with prices but not with the unobserved mean value ξ.

Adequate demand instruments W include political variables Pol_{zg} that affect the weight on consumers λ_{zg}, and therefore prices, but not the local demand for telephone. Thus, I include in W: *elect*, *% Democrats in PUC*, and *% Democrats in State Legislature*. Similarly, *Business/Residential Ratio* and *Competition* 95 affect the slackness of the profit constraint of the regulated ILEC, and therefore prices, but can be assumed uncorrelated with the demand unobservable ξ. The state averages of included demographic regressors in x can also be added to W. Prices in every local market are connected to the demand conditions in all other locations in the state through the presence of the common budget constraint. At the same time, the average demographic conditions can be assumed uncorrelated with the unobserved mean value in a particular local market. A parsimonious set of

[36] BLP (1995) impose a mean independence assumption $E[\xi|W] = 0$ that implies that any function of W is a potential instrument. The authors study then thoroughly the optimality of instruments with respect to the efficiency of estimation.

state controls includes *state asian %*, *state average income*, *state income flag* (indicator controlling whether the average state income is above the national average), *state rural %* and the interaction *%Rural · % Democrats in PUC*.[37] Finally, the firms plausibly choose debt as a function of demand and cost conditions, making the level of liabilities an invalid instrument.

The weights λ and unobserved costs mc are identified by the assumption of optimality of observed prices and the regulation models developed in sections 4 and 5.2. Given the marginal consumer surplus and profits implied for given parameters, the unobserved weight and cost components adjust to ensure that there is no beneficial deviation in the regulated price choice. If I incorporate HCPM cost data as in 5.2.2. and 5.2.3, the first order conditions are only used to identify λ.

Cost and political shifters include geographic and political factors that can be taken as exogenous from unobserved conditions in the telephone market such as $Total\ hhs(k)$, *Density*, *% Rural* or *% Poor*. See Section 6.3 for the detailed specifications. The variation of these exogenous variables with respect to weights and marginal costs identifies the parameters γ and ϕ.

5.4 GMM estimator and Inference

The derivation above allows to construct a GMM estimator, as in Hansen(1982), based on the moment conditions $E[\xi \cdot W] = 0$, $E[\omega \cdot Cost] = 0$ and $E[\eta \cdot Pol] = 0$ stated at the beginning of this section. The sample analogs of the moment conditions are collected into the vector $f \equiv (f_W, f_{Cost}, f_{Pol})$ where:[38]

$$f_W = \frac{1}{N} \cdot \sum_{n=1}^{N} \widehat{\xi}_n \cdot W_n$$

$$f_{Cost} = \frac{1}{P} \cdot \sum_{p=1}^{P} \widehat{\omega}_p \cdot Cost_p$$

$$f_{Pol} = \frac{1}{D} \cdot \sum_{d=1}^{D} \widehat{\eta}_d \cdot Pol_d$$

The system formed by the demand moments f_W is overidentified so it is not possible to make f exactly equal to zero. I solve then the program $\min_{\Theta_D, \Theta_S} f^T \cdot A \cdot f$ where A is a robust positive definite

[37] The HCPM cost measures are redundant given their correlation with geographic variables. Additional estimators including the HCPM cost proxy are available upon request.

[38] The exogenous shifters (*Cost*, *Pol*) and errors(ω, η) in the cost and policy moments depend on the choice between the models in sections 5.2. In particular, the cost moment f_{Cost} corresponds to equation (26) if HCPM data is used to estimate TC_{HCPM}. If mc is directly backed from (10) and (11), f_{Cost} corresponds to equation (7).

weight matrix.[39] The variance covariance matrix $\widehat{\Sigma}_\Theta$ of the estimated parameters $\hat{\Theta}_D \equiv (\widehat{\beta}, \widehat{\alpha})$ and $\hat{\Theta}_S \equiv (\widehat{\gamma}, \widehat{\phi})$ is obtained from the general GMM variance covariance formula. That is,

$$\widehat{\Sigma}_\Theta = (1/N)(\Gamma^T A\Gamma)^{-1}\Gamma^T AVA\Gamma(\Gamma^T A\Gamma)^{-1}$$

where Γ is the jacobian of the derivatives of moment conditions with respect to parameters in Θ_D and Θ_S. The term $1/N$ comes from the asymptotic scaling term $\sqrt{N}$ applied to all the moments in f. The expression in V corresponds to the variance covariance of moments. Formally,

$$\Gamma = \begin{bmatrix} \partial f_Z/\partial\Theta_D & 0 \\ \partial f_{Cost}/\partial\Theta_D & \partial f_{Cost}/\partial\Theta_s \\ \partial f_{Pol}/\partial\Theta_D & \partial f_{Pol}/\partial\Theta_s \end{bmatrix}$$

$$V = \begin{bmatrix} \frac{1}{N}\sum_{s=1}^{S}\Phi_s^T\Phi_s & 0 & 0 \\ 0 & \frac{N}{P}\cdot\sum_{p=1}^{P}(\omega_p\cdot Cost_p)^T(\omega_p\cdot Cost_p) & 0 \\ 0 & 0 & \frac{N}{D}\sum_{d=1}^{D}(\eta_d\cdot Pol_d)^T(\eta_d\cdot Pol_d) \end{bmatrix}$$

The block diagonal structure of V follows from the assumption of no correlation between demand, cost and policy moments. Formally, I assume that the following condition holds $E\left[Cost^T\cdot\omega\cdot\xi\cdot W\right] = E\left[Pol^T\cdot\eta\cdot\xi\cdot W\right] = E\left[Pol^T\cdot\eta\cdot\omega\cdot Cost\right] = 0$ (and the same zero covariance condition for the antisymmetric elements in V).[40] The expression $\Phi_s = \sum_{n=1}^{N_{zs}}\xi_n\cdot W_n$ for $n\in s$ allows for clustering of arbitrary form at the state level for the demand unobserved component ξ.

In section 5.2., I introduced in equation (24) the ratios of welfare weights λ^* for different consumer groups in a state s. The set of available weight differences is $\{\lambda_1^*, ..., \lambda_{TD}^*\}$, where $TD = D - number\ of\ states$, as one weight in each state must be used as base to form the differences. The variance of a particular difference in weights $\widehat{\sigma}^2_{\lambda^*}$ can be obtained from $\widehat{\Sigma}_\Theta$ by a simple application of the delta method because weight differences are a function of Θ_D and Θ_S. If I define the jacobian of a weight difference λ^* with respect to the parameters of the model as $\Gamma_{\lambda^*} = \partial\lambda^*/\partial\Theta$, it is possible to

[39] A is chosen a block diagonal matrix containing 2SLS weight matrix for the demand moments $\left(\sum W_n^T\cdot W_n\right)^{-1}$ and OLS weights for cost, $\left(\sum Cost_p^T\cdot Cost_p\right)^{-1}$, and policy moments,$\left(\sum Pol_d^T\cdot Pol_d\right)^{-1}$.

[40] A sufficient condition for this covariance structure to hold is the absence of correlation between unobserved shocks given exogenous variables, e. g., $E\left[\xi\cdot\omega|\ W, Cost\right] = 0$. Estimates are robust to more general assumptions on the covariance between demand and cost moments. Results are available upon request.

derive that:

$$\widehat{\sigma}^2_{\lambda^*} = \Gamma_{\lambda^*} \cdot \widehat{\Sigma}_{\Theta} \cdot \Gamma^T_{\lambda^*}$$

The same method can be applied to any function of $\{\lambda^*_1, ..., \lambda^*_{TD}\}$ to form suitable variances and *Chi-2* tests. I exploit this possibility to test the hypothesis that the sum of the squared weight differences is equal to zero. The test statistic is given by:

$$\chi_{\lambda^*} = (\lambda^*_1)^2 + ... + (\lambda^*_{TD})^2$$

If this test fails to reject, I interpret it as evidence in favor of no systematic bias between different consumer groups.

6 Results

6.1 Logit Demand Model

I present first a simple logit specification of demand without income effects as reference point for the presentation of the rest of results. Individual heterogeneity is limited to the idiosyncratic shocks ϵ_{in}. The mean value of service δ_n in a local market n is derived from the analytic inversion $\delta_n = \ln(s_n) - \ln(1 - s_n)$ used in classical analyses of the logit model such as McFadden (1974). The first column of the *All households* ($N = 6854$) panel of Table 2 contains the *OLS* estimates for demand parameters β, where included demand shifters are the local market household shares of different race groups (*%Black hhs, %Asian hhs, %Native hhs, %Other hhs*), median household income (*Median hh income*), measures of urban development (*%Rural*, *%MSA*), households in the local calling area (*LCA hhs*), measures of quality (*Customer complaints*, *Network Downtime*), regular prices (*Monthly_ 50, Connection (no subsidy)*) and subsidies (*Subsidy_ 50, Subsidy_ Connection*). The subsidies are obtained as the difference of the regular price and the discount. That is, *Subsidy_ 50* = *Monthly_ 50* - *Monthly_ 50(sub)* and *Subsidy_ Connection* = *Connection(no subsidy)* - *Connection(with subsidy).* The standard errors $Sd(\beta)$ are robust to the presence of clustering of arbitrary form at the state level.

The OLS coefficients in Table 2 for prices, *Monthly_ 50* (-0.021) and *Connection* (*no subsidy*) (-0.006), capture that monthly prices are more important in the adoption decision than the connection charge. The coefficients for subsidies, $Subsidy\_50$ (0.025) and $Subsidy\_Connection$ (0.012), show that the discount to the connection charge is more important than the charge itself. However, there are important caveats to the interpretation of this set of estimates. Firstly, the plausible endogeneity of prices makes OLS results biased and inconsistent. Endogeneity of $Monthly\_50$ and $Subsidy\_50$ results from the assumption that the regulator observes the component of the mean value unobserved to the econometrician, ξ_n, and she bases her price decision at least partly in demand conditions. This problem is not particular to the demand specification in the paper so endogeneity of monthly prices cannot be neglected as a by-product of the particular structural assumptions. On the contrary, endogeneity is not likely to be a serious problem for the connection fee as the small impact of these prices on demand and profits makes them a residual topic in the deliberations of the regulator. Also, empirical tests do not provide evidence of endogeneity of connection prices.[41]

The parameter estimates for the demographic controls are stable across specifications. The importance of controlling for racial factors suggested in the previous literature, Taylor et al. (1990), Riordan (2002) and Ackerberg et al. (2008), is confirmed with negative and significant coefficients for $\%Black\ hhs$ (-1.47), $\%Native\ hhs$ (-2.30) and $\%Other\ hhs$ (-2.44). $\%Asian\ hhs$ receives a positive coefficient (0.73) that is marginally significant. This positive sign could be due to the role of $\%Asian\ hhs$ as proxy for some measure of economic development or the highest willingness of Asian households to communicate with other households with phone. I do not explore the fundamental reasons of this effect in the current paper. The coefficients on $\%Rural$ (-0.34) $\%MSA$ (0.25) and $Median\ hh\ income$ (0.04) point to the reasonable result of higher demand for local telephone in wealthier communities with a higher degree of urban development. There is no meaningful relation between the quality controls and penetration given the insignificant coefficients obtained in *Customer complaints* (0.14) and $Network\ Downtime$ (0.07). Limited cross sectional variation in the quality proxies makes the identification of these parameters difficult. I will then not include these controls in my main specification.

The *IV* column of *All households* ($N = 6854$) panel in Table 2 considers endogenous *Monthly_ 50 (no subsidy)* and *Subsidy_ 50* and it uses the set of instruments in section 5.3. above to obtain 2SLS estimates. The correction of the endogeneity bias leads to increased price coefficients, *Monthly_ 50 (no subsidy)* (-0.088) and $Subsidy\_50$ (0.073), as expected from experience in the differentiated products literature and in line with Ackerberg et al. (2008). The increase in the price coefficients is translated

[41] Appendix C includes tests for endogeneity of *Connection* (*no subsidy*) and *Subsidy_Connection* as in Ackerberg et al. (2008). Strengh and validity analysis of the instruments is also provided.

into higher reported elasticity[42] of telephone penetration with respect to $Monthly\_50$ with a shift from 0.006 to 0.024. Interestingly the elasticity for the OLS estimates is close to the result of 0.005 in Hausman et al. (1993), which abstracts from endogeneity problems, and a significant increase in elasticity is observed from controlling for it as in Ackerberg et al. (2008). A Hansen *J-test* (6.38) based on efficient second stage GMM estimates does not reject the hypothesis that the model is not overidentified.

A more fundamental problem of the simple logit model is the assumption of homogeneous price sensitivity across households. The inadequacy of a constant marginal utility of income is well known from the differentiated products literature. The study at hand also presents the problem that the subsidies (*Subsidy_50*, *Subsidy_Connection*) only affect those households that are eligible for them. The simulation of household income in the next section will allow me to control for this particular problem. An alternative solution would center the study exclusively on a particular demographic group for which the price and income levels are homogenous. For example, the panel with $Poor\ Households$ ($N = 6374$) reproduces the analysis above exclusively for poor households under the assumption that these households make use of the subsidized prices. The net monthly price for poor households is denoted as $Monthly\_50(sub)$ and *Connection* (*with subsidy*). Looking at the IV specification results, I observe again higher price elasticity $Monthly\_50(sub)$ (0.026) and an effect of *Connection (with subsidy)*(-0.005) that is not significantly different from zero.

6.2 Logit Demand Model with individual income effects

This section presents the results of the full demand model described in section 4.1. The estimates for the controls affecting the mean value of service in a local market (*%Black hhs, %Asian hhs, %Native hhs, %Other hhs,* etc.) do not differ significantly from the basic logit model. The interest of the full model is rather in the possibility of estimating a different marginal utility for each level of income and assigning to each household the net price corresponding to its eligibility for Lifeline and Linkup. The variables $\widetilde{p}_{in}(m)$ and $\widetilde{p}_{in}(c)$ are obtained by subtracting the *Lifeline* and *Linkup* discounts, *Subsidy_50* and *Subsidy_Connection*, from regular prices $Monthly\_50$ and *Connection* (*no subsidy*) only for eligible low income consumers.[43] The results are presented in column (a) of Table 3. The effect of

[42] Elasticity at each wire center n is calculated at the expected value of the $x\beta$ index. A single measure is formed by averaging wire center elasticities with the wire center's share of total (poor) households as weight.

[43] I choose $y_i \leq \$20,000$ to classify a household as low income. Poverty threshold in 2000 ranged from $\$8,350$ to $\$17,050$ for households of size from 1 to 4 in the poverty guidelines. Eligibility for Lifeline and Linkup varies for each state but

monthly prices $\widetilde{p}_{in}(m)$ is negative and significant (-0.382) whereas the connection charge is negative but not significantly different from zero (-0.068). From the demand model in section 3, I obtain the price sensitivity for households with income (in thousands) y_i as $\frac{-0.382}{y_i}$. Furthermore, I compute the elasticity for each different level of income.

Figure 2. a. presents the elasticity of the probability of adoption to $\widetilde{p}_{in}(m)$ for income levels ranging from $\$5,000$ to $\$40,000$, maintaining the mean value of service $x\beta$ at the sample median values of x. Elasticity declines quickly as the level of income of the household increases and it is significantly higher for the lowest income levels.[44] The use of average elasticity masks this variation across income levels. The average market demand elasticity[45] for *All households* is (0.02), which represents an intermediate value between the elasticities for households in the low income and general population groups. The average market demand elasticities for *Eligible* and *Non Eligible* households are respectively given by (0.054) and (0.002). A Wald test for the squared difference of the elasticity for *All households* and *Non eligible* rejects the hypothesis of a zero difference between these two aggregate elasticities, showing the importance of controlling for variation in elasticity across income groups.

Figure 2. b. presents the results for a particular local market (observation 73 in South Carolina) in the sample, with relatively low penetration (0.88). The pattern of elasticities is similar to the calculation for the hypothetical local market in figure 2.a. but it is important to notice that the levels are higher. For example, a household with an approximate income of $\$24,000$ exhibits an elasticity close to 0.05 in the local market corresponding to figure 2.b. whereas it presents an elasticity below 0.01 for the hypothetical local market in figure 2.a.

The model estimates in column (b) of Table 3 account for the fact that participation in the subsidy programs is below 100% by assigning the discounted prices in every market only to a fraction of eligible consumers equal to the participation rate in the Lifeline program at the state level. This leads to a reduction of the estimated price coefficient to (-0.322). The coefficient for the connection turns positive (0.02) but it cannot be statistically distinguished from zero. This reduction in the coefficient is translated into a small change in the elasticities for *All households* (0.022) and *Eligible* (0.058).

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it is usually laxer than proof of poverty status (income at or below 135% or 150% of the poverty line,participation in welfare programs). It is not possible to control perfectly for eligibility with aggregate data but it is possible to check for the robustness of the results to different assumptions.

[44] Elasticty for households with income below $\$5,000$ ranges from 4.94 to 0.05. They were not included in the figure for scaling issues.

[45] A single measure is formed by averaging wire center elasticities with the wire center's share of total (poor) households as weight. The same method limited to eligible and non eligible households is applied for these alternative elasticity measures.

The increase in the prices for households excluded from the subsidy programs compensates for the smaller price coefficient to keep elasticity comparable to the results in column (a). The elasticity for *Non eligible* increases to (0.017) as more low income households enter into this average. Given the robustness of the results to the correction of the participation rate in *Lifeline*, I will use the base specification in column (a) of Table 3 for the remaining sections.[46]

6.3 Expected Marginal Cost

I explore different regressions of the total HCPM cost in a local market to estimate the regulator's expected marginal cost $E\left[mc_{jz} \mid \iota_s\right]$ for the specifications in 5.2.2 and 5.2.3. Cost shifters $Cost_p$ include the HCPM targets for residential, business and special access lines (*Res Lines, Bus Lines, Sa Lines*), geography (*Area, % Rural, %MSA*) and interactions. The HCPM target lines are valid exogenous regressors because they are based on population data and target levels of service in the HCPM rather than actual demand.

These regressions reproduce the cost estimation in Rosston et al. (2008) and they are in line with the estimation approach put forward in Gasmi et al. (2000). Model (a) in Table 4 simply regresses total cost in the number of residential, business and special access lines to obtain the average marginal cost for each type of line across the sample. Model (b) in Table 4 incorporates interactions with area (*Area·Res Lines, Area*·Bus Lines...) to obtain an estimate of marginal cost specific to each location. Model (c) in Table 4 further considers interactions between the different types of lines (*Res Lines·Bus Lines, Res Lines·Sa Lines*) to examine possible economies of scope. This is a simple implementation of equation (25) where function $g(\gamma, Cost_n)$ is assumed linear in the parameters. For example, Model (a) is given by:

$$TC_{HCPM,\ p} = \gamma_0 + \gamma_1 Res\ Lines_p + \gamma_2 Bus\ Lines_p + \gamma_3 Sa\ Lines_p + \gamma_4 Area_p + \omega_p$$

For this simple model, the marginal cost $\widehat{mc}_p$is simply equal to $\widehat{\gamma}_1$. Model (b) and Model (c) estimates of $\widehat{mc}_p$ are obtained analogously. In all specifications,[47] the average estimated marginal cost is close to \$23 with a standard error of at most \$2.6. Table 4 contains summary statistics of $\widehat{mc}_p$,

[46] Additional robustness checks based on different price proxies (*Monthly*_100) and alternative eligibility criteria (use of different income thresholds for eligibility as a function of state characteristics) yield comparable results that are available upon request.

[47] Additional specifications with %*Rural*, %*MSA* and other controls are available. Results are stable accross these specifications.

extended also to fixed costs FC. The latter do not play a role in estimation of welfare weights but they are included for completeness. Estimated $\widehat{FC}$ equals the sum of the regression constant and the term $\gamma \cdot Area_p$ so it should be interpreted with caution as it incorporates the average of the regression error. $\widehat{FC}$ is not a precise measure of fixed costs.

6.4 Alternative Regulation Models with unobserved costs

I consider first a model with a single weight λ_z and an unobserved cost correction mc_z for every zone z as presented in section 5.2.1. The results are presented in Table 5. The policy controls Pol_d considered include the price zone averages of $Total\ hhs$ (k), % *Rural* and % *Poor* whereas I choose the price zone averages of $Total\ hhs(k)$, household *Density*, % *Rural* and % MSA for cost controls $Cost_p$. This is a reasonable choice, as the cost of providing service is highly dependent on the geography of the local market. Given these assumptions, I can estimate the cost and welfare weight equations in (19) and (20). The results are presented in Table 5.

The estimates of policy parameters ϕ include $Total\ hhs(k)$ (0.0002), % *Rural* (-0.003), and % *Poor* (-0.26) against the common wisdom of a bias in favor of poor and rural areas. Only the variable % *Poor* and the constant are significant. A Wald test, $W-test\ Weights$, on the estimated sum of squared weight differences $\sum_{d=1}^{TD} (\lambda_d^*)^2$ cannot reject the hypothesis that there is no systematic difference in weights given a statistic value of 1.77 for a $\chi_2(1)$. The estimates for cost parameters γ reveal that less rural areas are assigned a higher cost given *Rural* (-0.24) and % MSA (1.84). The estimate of *Density* (-0.0004) and $Total\ hhs(k)$ (-0.05) are signed as anticipated as more dense and populated areas are expected to have lower marginal costs. Only the constant and % MSA terms are significant in the cost regressions. The estimated marginal cost is too close to \$ 0 and far from the HCPM benchmark of \$ 23 to be realistic. I suspect this unnatural estimate is to be attributed to misspecification coming from the assignment of a single weight to each area rather than allowing a weight λ_{z2} for low income and λ_{z1} for general population in a given zone z in state s. The current model is likely to attribute low costs rather than high consumer bias in favor of poor rural consumers to justify the prices in those regions. This model illustrates the limitations in the use of optimality conditions for estimation with limited cost information.

In order to overcome this limitation, I will move to a specification with different weights for eligible and non eligible consumers in line with section 5.2.2. I also include a variation in which the average cost of the HCPM model is employed as a crude estimate of the marginal cost per line $E\left[mc_{jz} \mid \iota_s\right]$. This *HCPM* AC^* specification is motivated as a robustness check for the possibility that the regulator's expectations are such that AC^* is used as a proxy for the true marginal cost MC^*.[48]

The panel (a) *Base scenario* of Table 6 contains the results for this new specification. The extra policy controls include now *Dummy Poor Weight* (I_{Poor}) that takes the value of one if the weight corresponds to a group of low income consumers and zero otherwise. I also include interactions of this dummy with price zone averages of *Elected Commission*, % *Democrats−Legislature*, % *Democrats−PUC*, *Total hhs*(k), % *Rural* and % *Poor*. The estimates are qualitatively comparable between the AC^* and MC^* specifications so I focus on the latter.

I obtain now that regulators reduce the weight on the general population and increase the weight on poor population in poor areas given significant estimates % *Poor* (-0.18) and % *Poor* $\cdot\, I_{Poor}$ (0.79). I do not find strong evidence in favor of the presence of rural bias with insignificant estimates % *Rural* (0.003) for the general population and % *Rural*$\cdot I_{Poor}$ (0.042) for the low income consumers.[49] The suppression of the downward bias for regular consumers in poor areas would lead to lower regular local telephone prices in accordance with the lower value of the service in those areas. On the contrary, poor consumers would observe an increase in prices if the bias is eliminated. The political variables interacted with I_{Poor} do not seem to have a significant effect as shown in Table 6. Finally, I note that the δ estimates for (*Constant*, *Total hhs(k), % Rural, % Poor*) in Table 5 and Table 6 are comparable. The lack of flexibility of the weights in the specification from 5.2.2. does not affect these estimates of the relation of weights and demographics for the general population.

Overall, the results for (a) *Base scenario* contradict the view that there is a general rural bias but point out to a bias limited to poor consumers. The importance of this bias is moderated by the fact that $W-test\ Weights$ fails to reject again that all weight differences are systematically zero with 2.34 for AC^* and 1.58 for MC^*. The % *Rural* or % *Poor* differences between zones are not big enough to conclude that there are systematic weight differences that are significant from a statistical point of view. The figure 3.a. plots the sorted differences in welfare weights and error bands (the weight λ_{11} is used as base to form the difference in each state). The figure suggests that the observed welfare weights are not significantly different from zero but $W-test\ Weights$ provides a more formal test.

[48] The criticism over the possible incorrectness of the HCPM estimates remains. However, the estimates of γ from (25) are not made inconsistent or biased due to the presence of measurement error in TC_{HCPM}. Then, the use of HCPM data should not be a problem for the main specification MC^* but it would affect more seriously the results for AC^*.

[49] Note that the estimates for δ affecting the general population in Table 5 and Table 6 are in line.

The panels (b) $Federal\ I$ and (c) $Federal\ II$ use the variations in the first order conditions of the regulatory problem considered in section 4.3. and 5.2.3. to reestimate the weights and policy parameters ϕ. The specification in $Federal\ I$ provides strong incentives for the regulator to increase the penetration among low income households and high cost areas. $Federal\ II$ gives moderate incentives to enlist low income households as described in section 4.3. The previous results on the effect of % *Poor* on bias are reversed and it seems that in areas with higher value of % *Poor*, I observe higher weight in favor of the general population and less weight in favor of low income population.

Looking at Table 6 $Federal\ I$ for MC^*, I observe the estimates % *Rural* (-0.012), % *Poor* (0.88), % $Rural \cdot I_{Poor}$ (0.064) and % $Poor \cdot I_{Poor}$ (-0.514). Only % *Poor* and % $Rural \cdot I_{Poor}$ are statistically significant in this subset of coefficients. Given the incentives to obtain funds from the federal Lifeline program, the observed prices in areas with high average number of poor implies a low weight on low income consumers versus the general population. This effect is however weak, as % $Poor \cdot I_{Poor}$ is not significant. The higher weight for poor consumers in zones with higher % *Rural* survives the change of specification. It is interesting to note that the estimates for % $Rural \cdot I_{Poor}$ (0.38) in the AC^* specification also remain positive and significant. I interpret that given the high AC^* in these areas, the relatively low level of prices for low income consumers requires a higher bias in their favor in addition to the incentive to obtain federal subsidies. Another interesting result is that democrat regulators are assigned higher weights for low income consumers with significant coefficients % $Democrats - PUC \cdot I_{Poor}$ (0.05) and % $Democrats - Legislature \cdot I_{Poor}$ (0.29). The $W - test\ Weights$ rejects the hypothesis of no systematic weight differences across consumer groups with value statistics equal to 28.13(1) for AC^* and 10.25(1) for MC^*. More informally, the figure 3.b. shows how the weight differences are further apart from zero under this specification. The conclusions under $Federal\ I$ are qualitatively robust to the specification of marginal cost (AC^* or MC^*) but estimated weights depend on the assumptions on the federal subsidy programs.

The results for the $Federal\ II$ specification are qualitatively comparable to $Federal\ I$ but the magnitude of the bias changes. For specification MC^*, I observe estimates % *Rural* (-0.08), % *Poor* (0.82), % $Rural \cdot I_{Poor}$ (0.17) and % $Poor \cdot I_{Poor}$ (-0.65). All theses coefficients are significant with the exception of % *Rural*. It is noteworthy that the coefficient on % $Rural \cdot I_{Poor}$ stays positive across all specifications (and significant for most) pointing towards the robustness of the rural poor bias. However, the size of % *Rural*. is relatively weak when compared with the effect of poor population % $Poor \cdot I_{Poor}$ so the rural bias does not seem to be the main distortion in the behavior of the regulator. With respect to $\%\ Poor$ and $\%\ Poor \cdot I_{Poor}$, both $Federal\ I$ and $Federal\ II$ imply that the regulator is favoring (positive coefficient on $\%\ Poor$) the general population in low income areas at the expense (negative coefficient on $\%\ Poor \cdot I_{Poor}$) of the low income population. A plausible explanation is that the regulator does no exploit fully the possibility to price discriminate between low income and general population. The regular prices in low income areas are lowered, favoring the general population, but the discounts on the poor population are not large enough to discard a relative bias against the poor population there. Again, the differences in weights are large enough to reject that there is no systematic bias with $W - test\ Weights$ statistics equal to 43.3(1) and 17.13(1). Figure 3.c. provides a graphical representation of this argument. The main difference with respect to $Federal\ I$ is that the political control $Elected\ Commission$ (0.15) turns significant together with $\%\ Democrats - Legislature$ (-0.6) and $\%\ Democrats - PUC$ (0.43). The signs are as expected with the exception of $\%\ Democrats - Legislature$. Given the lower speed of law making relative to PUC decisions, it is reasonable that $\%\ Democrats - Legislature$ is not as directly connected with regulation as the variables describing the PUC configuration and it captures some institutional feature of the state.

7 Policy Experiment

As noted in the introduction, the presence of cross subsidies in the structure of telephone prices has been the object of much interest for academics and practitioners involved in the telecommunications sector. Sections 1 and 2 examined the transition from a price structure with cross subsidies to a cost oriented price structure. This change has been presented either as a desirable goal that eliminates welfare reducing distortions or, on more practical terms, a necessary consequence of the entry of competitors. In this section, I examine the direct welfare effects of this class of residential telephone price realignments with the help of the formal model in Section 4. This model allows me to calculate the adjustment of residential demand, revenues and variable costs to these price changes. It is important to note that optimal prices are responsive not only to cost but demand conditions and the formal model allows to control for all these different factors. For a given profit requirement, optimal prices for high cost areas do not necessarily match the full average cost in those areas if consumers also exhibit a relatively weak demand.

This exercise takes as exogenous the location of the local networks and it focuses on price variations in line with the main policy discussion in the literature. It would be a different question to consider the suppression of certain local networks to avoid all the costs associated to them. This question exceeds the scope of the current paper as the disconnection of entire portions of the network is far from the center of policy debate due to political and legal restrictions. More importantly, the telephone network is already installed and a portion of the fixed costs are sunk so the relevant policy decision is the choice of prices that maximize welfare given this configuration.

The policy experiment only considers an adjustment of residential telephone prices rather than the full price structure of telecommunication services in each state. However, I argue this limited range of price changes is close to the set of choices available to a state regulator that sees how the competition for business customers limits her influence in that segment.[50] The limited exercise is relevant as it captures the consequences of price increases of regulators with limited power.

7.1 Cost Pricing Rules

I calculate the welfare and profit changes associated with a realignment of prices with marginal cost and average costs. These are simple rules that do not require solving an optimization problem. I present them first to set the structure of the counterfactual exercises. An increment of residential prices towards marginal or average residential costs per line will lead to a decrease in demand, which will bring for the firm both a reduction in revenues and variable costs. I compute variable costs with the marginal cost estimate in section 6.3. so $\widehat{CV}(\widehat{D}_n) = \widehat{mc}_n \cdot \widehat{D}_n$ for a local market n. This formulation captures that only a fraction of the cost is varying as demand shifts. This is still a long term perspective as it assumes that the marginal cost per line mc_n can be avoided as demand decreases. The results are presented in Table 7.

Marginal cost pricing maximizes welfare for a given network of local markets so I observe that the increase in the sum of welfare for of all the states $\Delta W =$ \$ 16.25 M is greater for this policy versus $\Delta W =$ \$ 10.5 M for average cost pricing. Given that the sample comprises a substantial portion of the local telephone market in the US (68 M households), this represents a small welfare distortion even if measured in annual terms (\$ 195 M and \$ 126 M). The changes in consumer surplus and profits are significantly higher with $\Delta \pi =$ \$ 717 M and $\Delta CS =$ \$ (700.5) M for marginal cost policy and $\Delta \pi =$ \$ 714 M and $\Delta CS =$ \$ (703.6) M for average cost policy. Figure 4.a. presents a scatter plot of

[50] The determination of wholesale prices is an alternative policy tool available to the regulator that is out of the scope of the current exercise. See Rosston et al. (2008).

the percentage increase in welfare and the percentage of rural population across states that provides cursory evidence of the greater welfare gains of moving to cost oriented prices in rural states. The magnitude of the changes is nonetheless small.

There is a high stake in the shift to cost oriented prices for the firm and consumers, as a sizable redistribution of surplus would follow from realigning prices with costs. This result is implied by the low average elasticity of demand. As prices increase from the current level, which allows a deficit in the residential segment, the consumers do not drop the service in significant numbers. The higher tariffs then increase the return that the firm obtains from each household of a network that stays basically constant. The average changes in penetration are $\Delta P_n = (0.026)$ and $\Delta P_n = (0.027)$ for marginal and average cost pricing as reported in Table 7.[51] I notice though that the decrease in expected penetration among low income consumers is substantially higher. For example, $\Delta P_n = (0.103)$ for the marginal cost pricing policy. The difference between the expected telephone adoption rate under the actual price regime and marginal cost pricing is plotted for the general population in Figure 4.b. and for low income consumers in Figure 4.c.[52] This provides a graphical illustration of the higher impact of the price increases on the low income consumers. It also provides some cursory evidence that the penetration declines are more acute in local markets with an already preexisting low penetration.

The small variation in total welfare seems to imply that the allocation problem associated to the tariff choice is a problem to be guided by equity considerations. However, the elimination of the deficit can allow to reduce the distortions in other sectors of the economy (business local telephone sector, long distance telephone sector,etc.) and lead to higher efficiency gains. It is not possible for me to estimate these gains precisely given the nature of my data set. Some basic calculations can be performed with estimates of the social cost of local telephone deficit. With a public funds multiplier of 1.3,[53] the additional efficiency gain associated with the reduction of deficit is \$ 215 M for marginal cost pricing and \$ 214.2 M for average cost pricing. The annual equivalents of these amounts are significant and approximately equal to $\$2,6$ M.

[51] Averages are calculated over the changes at the wire center level using the percentage over the total sample of households (poor households) in a wire center as weight for the changes in a particular wire center.

[52] In order to draw the Figures 4.b. and 4.c., I sort the observations by expected penetration under actual price regimes, Pen_actual and Pen_actual(poor), and I plot then these magnitudes together with expected penetration under the marginal cost regime, Pen_MC and Pen_MC(poor). I do so only for the observations in the centiles to get an appropriate scale in the plots.

[53] Snow and Warren (1996) find this is as an average estimate of the cost of public funds for OECD countries.

7.2 Alternative Regulators

I examine here the pricing policies that would be implemented by a regulator with no bias across consumers and without the presence of the federal subsidy programs. This regulator will set optimal Ramsey prices given the minimum profit requirements imposed on her and it will be possible to compare the outcomes of these counterfactual policies with the actual observed policies. If the profit requirement is set equal to the current level of deficit from residential telephone services, the welfare optimization problem corresponds to a regulator that tries to make use of the allowed deficit to maximize unweighted consumer surplus rather favoring specific groups. If the profit requirement is set to cover the total cost of providing residential service, welfare maximizing prices will provide the optimal adjustment to the elimination of the sources of cross subsidies. I have described in section 3 how different prices are set for each price zone and that this geographic unit aggregates multiple local markets. I will allow for pricing at the zone level in *Zone Regulator* scenarios and pricing at the market level in *Multi Market Regulator* scenarios when solving the optimization problems. This will provide the additional benefit of measuring the welfare impact of allowing for geographic price discrimination.

The elimination of the bias between different consumer groups is a move to the elimination of inefficient price distortions and it might be regarded a priori also as an advance towards a more equitable regulation policy. The application of the optimal regulation model allows to produce an actual estimate of the efficiency gain and the price variations. It is important to note that maximizing consumer surplus can lead to a decrease in prices for the general population partly compensated by an increase in the prices for the low income population. A household with median income is less likely to drop the service given a price increase and its expected consumer surplus decreases more than the corresponding surplus of a low income household. I observe this pattern in the *Zone Regulator I* scenario with $\Delta\widetilde{p}_{1n}(m)$ = \$ (3.9) and $\Delta\widetilde{p}_{2n}(m)$ = \$ 17.9. This policy change implies an increase in efficiency, ΔW = \$ 13.8 M but the fact that base rates are reduced at the expense of the low income consumers makes this policy difficult to implement in practice. The results in *Multi Market Regulator I* exhibit additional welfare gains associated to the added pricing flexibility with ΔW = \$ 15.8 M. The full set of outcomes is presented in the upper part of Table 8.

The scenario in *Zone Regulator II* sets the profit requirement of the firm as high as to cover the portion of costs allocated to residential service according to the following average cost rule .

$$\overline{\pi}_s = \sum_{z=1}^{Z_s}\sum_{j=1}^{N_{zs}} ac_{jz,HCPM} \cdot D_{jzg}$$

where $ac_{jz,HCPM}$ corresponds to average cost per line in the HCPM model. This implies a hike in profit requirements from a negative deficit to an amount over the variable costs of the firm. I observe that the increase in welfare $\Delta W = \$13.8$ M for *Zone Regulator II* is greater than the result for average cost pricing showing that there is a benefit in reacting to demand and average cost conditions even if aggregated to the price zone level. The scenario with *Multi Market Regulator II*.has an associated welfare gain of $\Delta W = \$\ 16.1$ M that is very close to the optimal solution of marginal cost pricing. The portion of imputed total cost in excess of variable costs is moderate (a local market average of $\$24,\ 000$) so the welfare distortion imposed by the need to break even with respect to marginal cost pricing is small.

8 Conclusion

This article shows with an empirical study of local residential telecommunication services how structural econometric models can be used to recover regulators's preferences. The analysis requires only public market data and well-understood IV-GMM techniques as in BLP (1995). The presented framework can then be useful for regulators and researchers without survey data and limited resources.

The estimated distribution of price elasticities as a function of income presents a rapid decrease towards zero as household income increases. Demand results are robust to controlling for household differences in participation in subsidy programs. The results show that low income households have higher price sensitivity than the average household, as suggested in Ackerberg et al. (2008).

The regulation model separates demand and cost factors precisely from actual differences of regulator's weights across consumers with different incomes and locations. The analysis shows no evidence of a bias in favor of the general population of rural areas but it offers some support for the presence of a bias in favor of poor consumers in rural areas. The estimated effect of the percentage of poor consumers of an area on the relative weights depends on the estimated model. For the realistic assumption that state regulators do not internalize fully the costs of federal low-income subsidies, I observe that low income consumers are disfavored in poor areas. The negative relative bias on low income consumers is compensated in states with a Democrat and direct election PUC by the higher state-wide average weight placed on low income consumers. Under several plausible specifications, a joint test on weight differences rejects the hypothesis that they are systematically equal to zero.

The confirmation of the existence of state regulator bias is important for the implementation of federal policies and it provides some justification for the federal subsidy programs if these are oriented to correct biases in state policy. This information can be relevant for the extension of universal service subsidy programs to wireless and broadband Internet services. The importance of a proper structure of Broadband Universal Service will be increasing as Internet and Internet telephony consolidate further. The experiments in the last section quantify a small direct welfare effect of regulatory bias on local residential services but an important redistribution between residential consumers and the firm. If the implementation of new subsidy programs is decentralized to state regulators, we can expect the cross-consumer bias to lead the implemented outcome away from the first best solution. To the extent that the demand for wireless and new Internet services is as inelastic as the demand for local telephone in the past, the direct welfare impacts can also be expected to be moderate. Whether this is effectively the case is a question left for future research as better data on the broadband and wireless sector become available.[54]

9 Appendix A- Additional Data Description

The first part of the appendix contains the definitions of demographic variables and information on the use of census data. The second part details the data on regulator's characteristics, competition and the price setting process.

9.1 Markets and Demographic Data

The data set is the result of matching the demographic information from the United States Census (2000) to data on regulation policy at the local market level. This combination is made possible by use of the Claritas (2003), which contains a cross reference of census block groups, CBGs henceforth, and wire centers. The CBG is the fines geographic level at which the US Census 2000 is disclosed. The average size of a CBG is 1,500 persons.

[54] The FCC increased in year 2008 the filing requirements of broadband providers to include subscribership breakdown at the census tract level. See http://www.fcc.gov/form477/censustracts.html

Local market demographics formed from the United States Census (2000) include total number of households, *Total hhs*, classification of total households by race groups, *%Black hhs, %Asian hhs, %Native hhs* and *% Other hhs* (*%White hhs* is recovered by subtracting from one the sum of the percentages for the other races), percentage of rural households, % *Rural*, percentage of poor households, *% Poor hhs*, *Median hh income (k)* and percentage of households in a Metropolitan Statistical Area (MSA), % *MSA*. A MSA is a geographic entity designated by the Census to represent core urban areas with population of at least 50,000 persons. I use this variable as a proxy for urban development and economic activity.

The United States Census (2000) allows me to construct total telephone penetration (percentage of total households with telephone), *Tel Pen Total*, and the joint distribution of income and race at the local market level. I add this data to the original Ackerberg et al. (2008) data set to characterize the demand conditions for the general population beyond the poor household group analyzed by Ackerberg et al.(2008). Telephone penetration for poor households, *Tel Pen Poor*, is constructed by allocating to CBGs data at the Census Tract level of the US Census 2000. The Census Tract is a broader geographical unit than the CBG.

9.2 Regulator's characteristics and tariff setting

The National Association of Regulatory Utility Commissioners provides in NARUC (2002) data for each state public utility commission (PUC) on the percentage of democrats, % *Democrats in PUC*, and the formation mechanism (election versus appointment), *Elected Commission*. This provides a basic political profile for each commission. In addition, *% Democrats in State Legislature*, also informs of the political characteristics of the state.

Competition in residential local telephone has remained moderate despite the TA 96, with a national average of 2% of residential lines provided by CLECs in year 2000. Entry in local telephone has focused on the business segment, which contains a higher number of sizeable high value customers. The profit derived from the business segment contributes to break even by ILECs and it provides slack to the regulator to maintain low residential revenues. The relative size of the business and residential segments (measured as the rate of business to residential lines in the state), *Business/Residential Ratio*, and the degree of competition (measured with the percentage of lines provided by competitors and the early presence of competition in 1995), % *CLEC lines* and *Competition in* 1995, are proxies for the slackness in the budget constraint faced by the regulator.

The data set contains not only the tariffs described in section 3.1. but also the line counts employed by the regulators in the tariff setting process. State regulators commonly follow a value-of-service methodology[55] to set prices by which they firstly assign wire centers into geographic groups denominated as local calling areas (LCAs), classify the LCAs into rate groups according to the number of lines and then set different prices for different rate groups. Some states follow alternative approaches and assign a single price across the state or allow prices to depend explicitly on costs. The number of households in each LCA, $LCA\ hhs$, is used as a proxy for network value.

10 Appendix B- Mean Value Algorithm

I detail in this appendix the algorithm used to implement the contraction in (14). As presented in section 5.1., the algorithm in Nevo(2000, 2001) would apply at each iteration step of (14) to all 6854 observations until convergence of the observation requiring the longest time is achieved. There is an absolute speed gain in stopping the process (14) for observations at which convergence is achieved. Without this correction, the process is simply not usable as convergence time of (14) is measured in hours. For example, less than 1% of the sample exceeds a telephone penetration level higher than 0.999 but it would force thousands of additional iterations for all 6854 observations if this precaution is not taken. I employ then the following procedure,

Mean Value (δ_n) algorithm

For a total number of N local markets, define an appropriate norm $\|.\|$over differences[56] $\delta_T^{it+1} - \delta_T^{it}$. Then,

Step 0: Set $T = N$, define number of iterations $it\_step = 100$ and choose tolerance level tol.

Step 1: Apply step (14) for a number of iterations it_step.

Step 2: Check whether $\left\|\delta_T^{it\_step} - \delta_T^{it\_step-1}\right\| < tol$. If "*yes*" stop the procedure. If "*no*", proceed to step 3.

Step 3: Save $\delta_{T_{tol}}^{it\_step}$ for local markets $\delta_{T_{tol}}^{it\_step} \subseteq \delta_T^{it\_step}$ such that $\left\|\delta_{T_{tol}}^{it\_step} - \delta_{T_{tol}}^{it\_step-1}\right\| <$

[55] This description follows Rosston and Wimmer (2005) where more detailed analysis of the rate making procedure can be found.

[56] The norm $\|.\|$ is defined as the $\max\left|\delta_n^{it+1} - \delta_n^{it}\right|$ across $n \in \{1, 2, ..., N\}$. The symbol δ_T^{it} denotes the vector it of mean values $(T \times 1)$ for T wire centers.

tol.

Step 4: Use $\delta_{T_{no}}^{it\_step} \subseteq \delta_{T}^{it\_step}$ such that $\left\| \delta_{T_{no}}^{it\_step} - \delta_{T_{no}}^{it\_step-1} \right\| > tol$ to set $\delta_T^1 = \delta_{No}^{it\_step}$ and $T = T_{no}$. Increase the number of iterations to $it\_step = it\_step + 50$. Revert to step 1.

There is also a time cost of selecting and saving observations that achieve convergence. I have chosen to increase the number of iterations by 50 after each stop and obtain satisfactory results. It might be of independent interest to examine the computational gains of alternative schemes. Computational procedures considered in Su and Judd (2008) and applied to BLP demand estimation by Dube et al. (2008) might also improve the computation of mean value.

11 Appendix C- Analysis of Instrumental Variables

In this section, I present the analysis of the relevance of the set of instruments employed in section 5 and endogeneity of monthly and connection charges. The statistics were obtained with the ivreg2 module for Stata developed by Baum et al. (2007). See this paper and Stock, Wright and Yogo (2005) for guidance to the weak IV literature.

The results in Table C1 column (a) correspond to the to the IV^* specification for *All households* in Table 3. It seems that proposed set of instruments is strong for *Monthly_50 (no subsidy)* with high partial R^2 (0.46) and F statistic (24.62) but it is not fully satisfactory for *Subsidy*_50 with an F statistic below the threshold value of 10 accepted as a rule of thumb in the weak instruments literature from results in Stock and Wright (1997). The use of cluster-robust standard errors blurs the meaning of this comparison as the standard test results are developed for the case of i.i.d. errors.[57] Given this uncertainty, I perform tests robust to the presence of weak instruments for the joint significance of $Monthly\_50$ (*no subsidy*) and *Subsidy*_50. Anderson-Rubin Wald test and Stock-Wright LM statistic reject the hypothesis of no joint significance of the coefficients on the monthly charges.

Table C1 column (b) considers an alternative specification with *Connection* (*no subsidy*) and *Subsidy_Connection* as additional endogenous variables. An endogeneity test based on the orthogonality conditions as described in Baum (2007) rejects the hypothesis of exogenous $Monthly\_50$ (*no subsidy*) and *Monthly_50 (no subsidy)* given a value of the statistic (6.65). An analogous test of the joint endogeneity of all the price variables fails to reject (7.56). A test of endogeneity of *Connection* (*no subsidy*)

[57] Stock and Yogo (2001) develop a rigorous test for the presence of weak instruments but it also excludes the presence of clustering in the errors. The comparison of suitable Kleibergen-Paap statistics to critical values of Yogo and Stock is not easily interpretable.

and $Subsidy\_Connection$ given endogenous $Monthly\_50$ (*no subsidy*) and *Monthly_ 50 (no subsidy)* fails to reject the null hypothesis of exogeneity (5.42). We have thus no evidence in favor of endogenous connection charges. However, weak instruments can affect the power of the endogeneity test and the proposed set of instruments seems weak for these new variables with partial R^2 values (0.0894) and (0.1118) and F statistic values (2.46). Given the theoretical reasons in Section 4 and the absence of a conclusive test rejecting exogeneity of $Connection$ (*no subsidy*) and $Subsidy\_Connection$, I limit myself to specifications where only $Monthly\_50$ (*no subsidy*) and $Subsidy\_50$ are considered endogenous. The robust Anderson-Rubin Wald test rejects again the hypothesis of no joint significance but the Stock-Wright LM statistic does not reject in this specification.

The bottom part of Table A1 reproduces the analysis for the poor population and it obtains analogous results with evidence in favor of the endogeneity of the monthly fee of low income households $Monthly\_50$(*with subsidy*) and strength of the instruments used for this variable. I do not repeat the analysis for the top part of the table and the reader is referred directly to Table A1.

Table 1 - Summary Statistics

	All Wires		Wires (<100%)	
N	7118		6854	
(a)	Mean	Sd	Mean	Sd
Tel Pen Total	0.971	0.030	0.970	0.030
Tel Pen Poor	0.923	0.063	0.920	0.063
Total hhs	9646	12140	9944	12268
% Black hhs	0.097	0.172	0.100	0.175
% Asian hhs	0.016	0.036	0.016	0.036
% Native hhs	0.008	0.033	0.008	0.033
% Other hhs	0.041	0.068	0.041	0.068
% Rural	0.397	0.408	0.391	0.407
% MSA	0.630	0.479	0.626	0.480
% Poor hhs	0.123	0.079	0.125	0.078
Median hh income (k)	43.664	17.246	42.998	16.588
(b)	Mean	Sd	Mean	Sd
% Democrat in State Legislature	0.541	0.130	0.540	0.128
% Democrats in PUC	0.347	0.271	0.348	27.325
Elected Commission	0.168	0.374	0.174	0.379
Business/Residential Ratio	0.577	0.141	0.575	0.142
Competition in 1995	0.155	0.362	0.154	0.361
% CLEC lines in 1999	0.044	0.019	0.042	0.016
% CLEC residential lines in 1999	0.021	0.020	0.020	0.020
Monthly_0	11.176	2.315	11.167	2.307
Monthly_50	13.588	2.495	13.575	2.480
Monthly_100	15.815	2.747	15.781	2.717
Monthly_200	16.839	3.225	16.802	3.217
Monthly_0(sub)	3.203	2.048	3.218	2.048
Monthly_50(sub)	5.066	2.433	5.071	2.443
Monthly_100(sub)	7.277	3.077	7.257	3.081
Monthly_200(sub)	8.498	4.125	8.485	4.139
Connection (no subsidy)	36.163	11.336	36.103	11.311
Connection (with subsidy)	12.465	7.532	12.506	7.553
LCA hhs	228450	420021	230782	424999
(c)	Mean	Sd	Mean	Sd
Average cost per line	38.060	27.627	37.872	27.424
Complaints per 1000 lines	0.336	0.397	0.337	0.396
Network Downtime	1.464	19.537	1.442	18.974

Notes: In panel (b), variables from % *Democrats in State Legislature* to % *CLEC residential lines in* 1999 are reported at the state level. Standard errors of this latter variable and % *CLEC lines* miss observations for AZ, AR, ID, IA, KS, KY, ME, NE, NV, NJ, NM, ND, OK, RI, SC, SD, WV.

Table 2 - Logit Demand Estimation

All households (N=6854)				
	OLS		IV*	
	β	Sd(β)	β	Sd(β)
Constant	2.514	0.340***	2.891	0.407***
Monthly_50 (no subsidy)	-0.021	0.024	-0.088	0.026***
Subsidy_50	0.025	0.024	0.073	0.051
Connection (no subsidy)	-0.006	0.007	-0.001	0.007
Subsidy_Connection	0.012	0.007	0.011	0.007
% Black hhs	-1.470	0.162***	-1.515	0.184***
% Asian hhs	0.729	0.437*	0.219	0.528
% Native hhs	-2.303	0.459***	-1.918	0.406***
% Other hhs	-2.441	0.757***	-2.803	0.706***
LCA hhs (M)	0.091	0.074	0.112	0.081
% Rural	-0.341	0.054***	-0.350	0.054***
Median hh income (k)	0.038	0.004***	0.037	0.002***
% MSA	0.251	0.051***	0.246	0.057***
Customer complaints	0.142	0.105	0.184	0.126
Network downtime	0.068	0.056	0.099	0.076
Elasticity: *Monthly_50 (no subsidy)*	0.006	0.007	0.024	0.007***
R2	0.667		0.652	
Hansen J-Stat			6.378(8)	

Poor households (N=6374)				
	OLS		IV*	
	β	Sd(β)	β	Sd(β)
Constant	2.165	0.242***	2.398	0.226***
Monthly_50 (with subsidy)	-0.024	0.018	-0.065	0.024***
Connection (with subsidy)	-0.006	0.007	-0.005	0.006
% Black hhs	-1.030	0.147***	-1.069	0.156***
% Asian hhs	2.577	0.604***	2.329	0.651***
% Native hhs	-1.931	0.476***	-1.652	0.440***
% Other hhs	-1.588	0.678**	-1.834	0.645***
LCA hhs (M)	0.190	0.055***	0.212	0.050***
% Rural	-0.329	0.064***	-0.334	0.063***
Median hh income (k)	0.018	0.003***	0.018	0.002***
% MSA	0.178	0.051***	0.176	0.053***
Customer complaints	0.120	0.107	0.149	0.106
Network downtime	0.055	0.056	0.065	0.053
Elasticity: Monthly_50 (with subsidy)	0.009	0.013	0.026	0.058
R2	0.379		0.367	
Hansen J-Stat			6.297(9)	

Table 3 - Logit Demand Estimation (with individual heterogeneity)

N	6854			
	(a)		(b)	
f	188.34		208.07	
	β	Sd(β)	β	Sd(β)
Constant	3.170	0.286***	3.189	0.335***
% Black hhs	-1.377	0.174***	-1.314	0.173***
% Asian hhs	0.595	0.526	0.459	0.513
% Native hhs	-1.925	0.362***	-2.293	0.532***
% Other hhs	-2.909	0.813***	-3.025	0.798***
LCA hhs (M)	0.150	0.045***	0.149	0.074**
% Rural	-0.376	0.063***	-0.400	0.064***
% MSA	0.227	0.055***	0.213	0.053***
Median hh income (k)	0.032	0.003***	0.032	0.004***
	α	Sd(α)	α	Sd(α)
$\widetilde{p}_{in}(m)$	-0.382	0.150**	-0.322	0.092***
$\widetilde{p}_{in}(c)$	-0.068	0.052	0.020	0.030
	$\varepsilon_{\widetilde{p}_{in}(m)}$	Sd($\varepsilon_{\widetilde{p}_{in}(m)}$)	$\varepsilon_{\widetilde{p}_{in}(m)}$	Sd($\varepsilon_{\widetilde{p}_{in}(m)}$)
All hhs	0.020	0.012*	0.022	0.006***
Eligible hhs	0.054	0.032*	0.058	0.024**
Non eligible hhs	0.002	0.001*	0.017	0.004***
$Wald_{\_elas}$	2.738(1)*		3.64 (1)*	

Table 4 - Marginal Cost Estimation with HCPM data

N	7118					
	(a)		(b)		(c)	
	β	Sd(β)	β	Sd(β)	β	Sd(β)
Constant	74238	1092***	58089	1010***	57951	1094***
Res Lines	23.021	0.085***	21.810	0.073***	21.038	0.113***
Bus Lines	14.919	0.177***	14.671	0.148***	13.998	0.236***
Sa Lines	10.108	0.184***	10.923	0.150***	14.007	0.276***
Area			87.026	4.847***	87.483	4.824***
Area·Res Lines			0.013	0.001***	0.016	0.001***
Area·Bus Lines			0.041	0.003***	0.037	0.003***
Area·Sa Lines			-0.028	0.002***	-0.033	0.002***
Res Lines·Bus Lines					0.00004	0.00001***
Res Lines·Sa Lines					-0.00004	0.00001***
Bus Lines·Sa Lines					-0.00003	0.00001***
R2	0.9829		0.9900		0.9903	
MC Res Lines						
Average			23.218		22.866	
Standard deviation			2.127		2.641	
Minimum			21.810		18.516	
Maximum			63.726		73.390	
FC Res Lines						
Average			67563		67474	
Standard deviation			14313		14388	
Minimum			58089		57951	
Maximum			340196		341538	

Table 5 – Regulator Preferences and Cost Estimation

N,N_mc,N_pol	6854,156,156	
	ϕ	Sd(ϕ)
Constant	0.0109	0.0039***
Total hhs (k)	0.0002	0.0002
% Rural	-0.0033	0.0051
% Poor	-0.2580	0.1115**
	ϕ	Sd(ϕ)
Constant	1.7689	0.9491*
Total hhs (k)	-0.0458	0.0485
Density	-0.0004	0.0003
% Rural	-0.2428	1.2194
% MSA	1.8356	0.7404**
R2 Weights	0.7210	
R2 Cost Correction	0.0589	
W-test Coefficients	14.2364(4)*	
W-test Weights	1.7713(1)	

Table 6 – Regulator Preferences Estimation

N,N_pol	6854,312

(a) Base Scenario

	AC^{**}		MC^{**}	
	ϕ	Sd(ϕ)	ϕ	Sd(ϕ)
Constant	-0.0028	0.0194	0.0137	0.0138
Total hhs (k)	0.0012	0.0009	0.0002	0.0004
% Rural	0.0525	0.0258**	0.0028	0.0096
% Poor	-0.1576	0.1064	-0.1805	0.0855**
I_{Poor}	-0.0516	0.0574	0.0097	0.0301
Elected Commission$\cdot I_{Poor}$	0.0563	0.0518	0.0201	0.0241
% Democrats-Legislature$\cdot I_{Poor}$	-0.1042	0.1204	-0.0074	0.0566
% Democrats-PUC$\cdot I_{Poor}$	0.0399	0.0373	0.0178	0.0160
Total hhs (k)$\cdot I_{Poor}$	-0.0010	0.0017	-0.0005	0.0009
% Rural $\cdot I_{Poor}$	0.2882	0.1012***	0.0416	0.0303
% Poor$\cdot I_{Poor}$	1.2206	0.3851***	0.7895	0.2701***
R2	0.721		0.857	
W-test Coefficients	17.1228(11)		28.005(11)***	
W-test Weights	2.334(1)		1.5837 (1)	

(b) Federal I

	AC^{**}		MC^{**}	
	ϕ	Sd(ϕ)	ϕ	Sd(ϕ)
Constant	-0.0302	0.0228	-0.0086	0.0159
Total hhs (k)	0.0003	0.0011	-0.0010	0.0005**
% Rural	0.0503	0.0371	-0.0117	0.0132
% Poor	0.8705	0.1237***	0.8792	0.0848***
I_{Poor}	-0.5273	0.0700***	-0.4873	0.0432***
Elected Commission$\cdot I_{Poor}$	0.0684	0.0646	0.0166	0.0237
% Democrats-Legislature$\cdot I_{Poor}$	0.1261	0.1699	0.2931	0.0811***
% Democrats - PUC$\cdot I_{Poor}$	0.0631	0.0502	0.0492	0.0218**
Total hhs (k)$\cdot I_{Poor}$	-0.0003	0.0023	0.0009	0.0010
% Rural$\cdot I_{Poor}$	0.3784	0.1458***	0.0639	0.0350*
% Poor$\cdot I_{Poor}$	-0.0170	0.4694	-0.5135	0.3211
R2	0.7768		0.9495	
W-test Coefficients	1726(11)***		1006 (11)***	
W-test Weights	28.1269 (1) ***		10.2457(1)***	

Table 6 – Regulator Preferences Estimation (contd.)

N,N_pol	6854,312

(c) Federal II

	AC^{**}		MC^{**}	
	ϕ	Sd(ϕ)	ϕ	Sd(ϕ)
Constant	-0.0373	0.0403	-0.0097	0.0395
Total hhs (k)	-0.0005	0.0015	-0.0019	0.0015
% Rural	-0.0168	0.0482	-0.0809	0.0473
% Poor	0.7991	0.1530***	0.8217	0.1495***
I_{Poor}	-0.0893	0.0753	-0.0438	0.0571
Elected Commission$\cdot I_{Poor}$	0.1943	0.0591***	0.1485	0.0371***
% Democrats-Legislature$\cdot I_{Poor}$	-0.7131	0.1427***	-0.6113	0.0990***
% Democrats - PUC$\cdot I_{Poor}$	0.4222	0.0463***	0.4293	0.0341***
Total hhs (k)$\cdot I_{Poor}$	0.0017	0.0025	0.0028	0.0018
% Rural$\cdot I_{Poor}$	0.4494	0.1329***	0.1740	0.0533***
% Poor$\cdot I_{Poor}$	-0.2371	0.4701	-0.6481	0.3457*
R2	0.6616		0.6817	
W-test Coefficients	390.2671(11)***		361.4437(11)***	
W-test Weights	43.3011(1)***		17.1286(1)***	

Table 7 - Cost Oriented - Pricing Rules

(a) Average Cost Pricing

	Total (in M dollars)	Average (in dollars)
ΔCS	(703.5905)	(102,654)
$\Delta\pi$	714.1037	104,188
ΔW	10.5132	1,534
$\Delta\widetilde{p}_{1n}(m)$		9.5393
$\Delta\widetilde{p}_{2n}(m)$		17.9658
ΔP_n		(0.0266)
ΔP_n (*low income*)		(0.1058)

(b) Marginal Cost Pricing

	Total (in M dollars)	Average (in dollars)
ΔCS	(700.4983)	(102,203)
$\Delta\pi$	716.740	104,572
ΔW	16.2473	2,370
$\Delta\widetilde{p}_{1n}(m)$		9.269
$\Delta\widetilde{p}_{2n}(m)$		17.851
ΔP_n		(0.0256)
ΔP_n (*low income*)		(0.1036)

Note: All Average column results are measured in dollars except P_n, which is measured in percentage points

Table 8 - Counterfactual Regulatory Schemes

(a) Zone Regulator-I

	Total (in M dollars)	Average (in dollars)
ΔCS	13.2873	1,939
$\Delta \pi$	.	.
ΔW	13.2873	1,939
$\Delta \widetilde{p}_{1n}(m)$		(3.9018)
$\Delta \widetilde{p}_{2n}(m)$		17.512
ΔP_n		(0.0217)
ΔP_n (*low income*)		(0.1255)

(b) Zone Regulator-II

	Total (in M dollars)	Average (in dollars)
ΔCS	(869,77)	(126,899)
$\Delta \pi$	883.58	128,914
ΔW	13.8052	2,014
$\Delta \widetilde{p}_{1n}(m)$		9.343
$\Delta \widetilde{p}_{2n}(m)$		17.872
ΔP_n		(0.0296)
ΔP_n (*low income*)		(0.1278)

(c) Multi Market Regulator -I

	Total (in M dollars)	Average (in dollars)
ΔCS	15.8127	2307.06
$\Delta \pi$	.	.
ΔW	15.8127	2307.06
$\Delta \widetilde{p}_{1n}(m)$		(3.0151)
$\Delta \widetilde{p}_{2n}(m)$		17.1840
ΔP_n		(0.0244)
ΔP_n (*low income*)		(0.1023)

(d) Multi Market Regulator -II

	Total (in M dollars)	Average (in dollars)
ΔCS	(867,473)	(126,563)
$\Delta \pi$	883.58	128,914
ΔW	16.1089	2350.28
$\Delta \widetilde{p}_{1n}(m)$		12.1750
$\Delta \widetilde{p}_{2n}(m)$		17.9558
ΔP_n		(0.0260)
ΔP_n (*low income*)		(0.1040)

Table C1 – Instruments Analysis

All Households		
	(a)	(b)
Shea's Partial R2		
Monthly_50 (no subsidy)	0.4623	0.2391
Subsidy_50	0.3264	0.2303
Connection (no subsidy)		0.0894
Subsidy_Connection		0.1118
F-Stat	df = (10,43)	
Monthly_50 (no subsidy)	24.62***	21.45***
Subsidy_50	6.82***	5.63***
Connection (no subsidy)		2.46 **
Subsidy_Connection		2.46**
WI Robust Significance Test	df = (10)	
Anderson-Rubin Wald test	42.78***	52.47***
Stock-Wright LM statistic	15.66*	13.32
Endogeneity	df = 2	df = 4, 13
Ho: All Exogenous	6.65**	7.56
Ho: Monthly Endogenous		5.42

Poor Households		
	(c)	(d)
Shea's Partial R2		
Monthly_50 (with subsidy)	0.387	0.299
Connection (with subsidy)		0.126
F-Stat	df = (10,43)	
Monthly_50 (with subsidy)	12.74***	10.49***
Connection (with subsidy)		2.36**
WI Robust Significance Test	df = 10	
Anderson-Rubin Wald test	59.24***	64.86***
Stock-Wright LM statistic	15.19	13.51
Endogeneity	df = 1	df = 2, 13
Ho: All Exogenous	4.882**	5.798*
Ho: Monthly Endogenous		4.758

Figure 1. a. Telephone Penetration (Alabama)

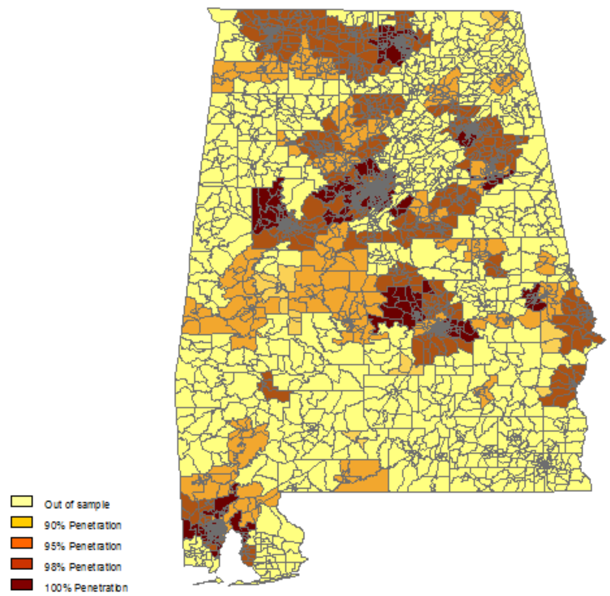


Figure 1. b. Telephone Penetration (New York)

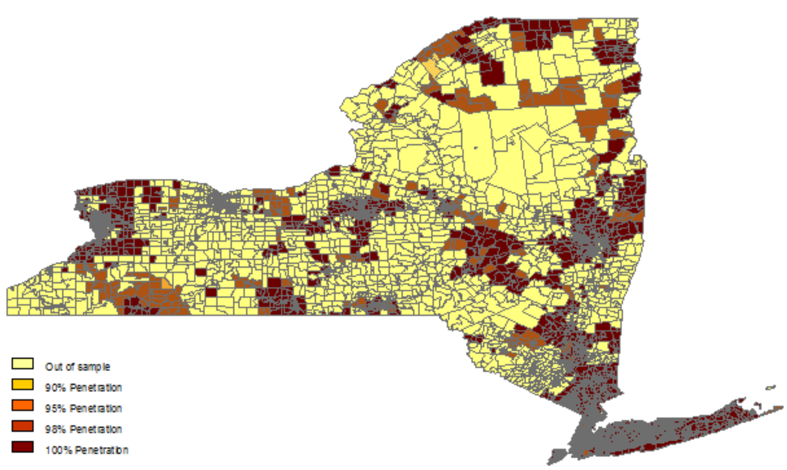
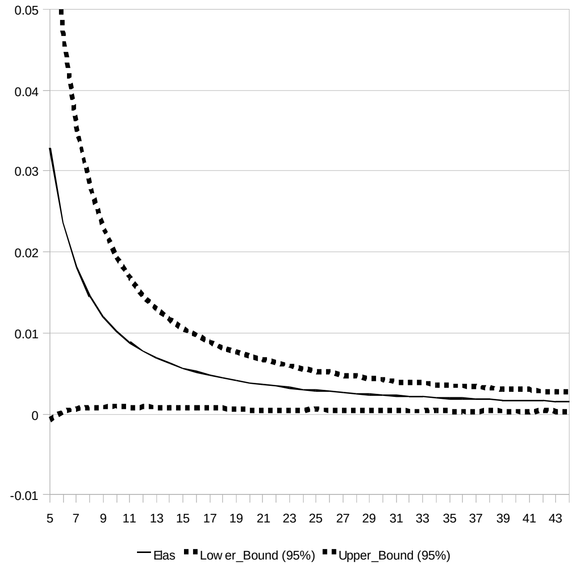
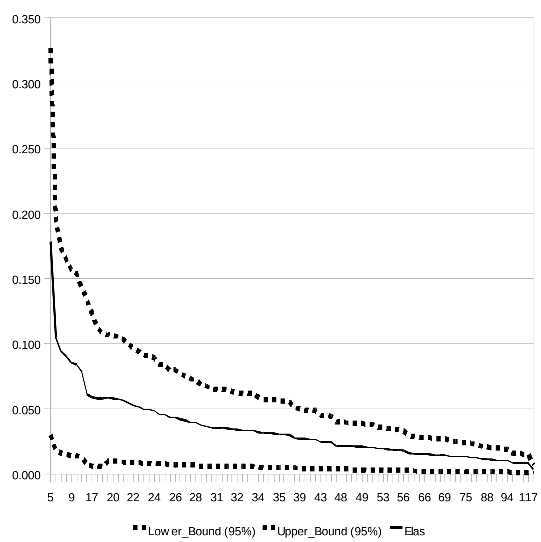


Figure 2. a. Price Elasticity Distribution (Median Local Market)



Note: The X-axis represents the households income (k) and the Y-axis represents price elasticity

Figure 2. b. Price Elasticity Distribution (Low Penetration Local Market)



Note: The X-axis represents the households income (k) and the Y-axis represents price elasticity.

Figure 3.a - Base Case-Differences in Consumer Weights (Logs)

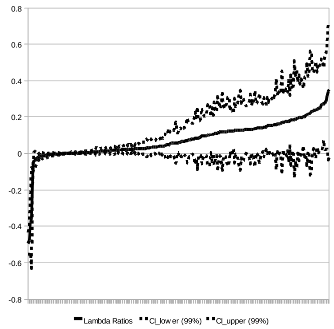


Figure 3.b - Federal I-Differences in Consumer Weights (Logs)

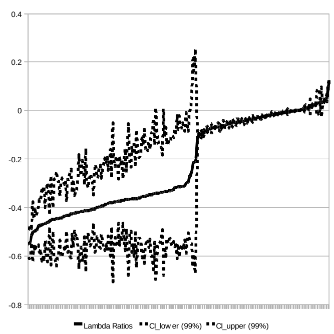


Figure 3.c - Federal II-Differences in Consumer Weights (Logs)

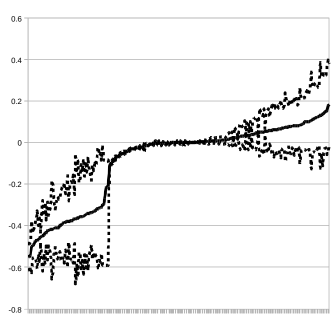
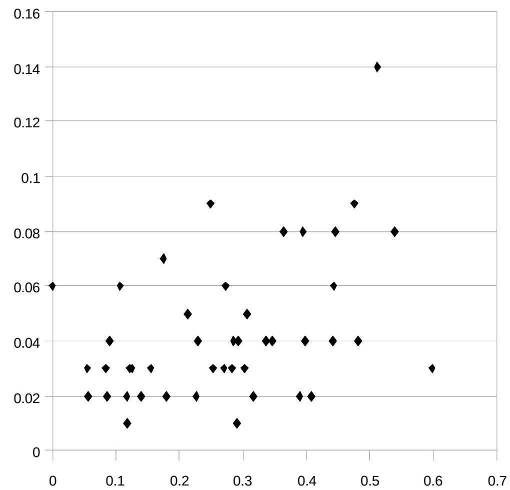
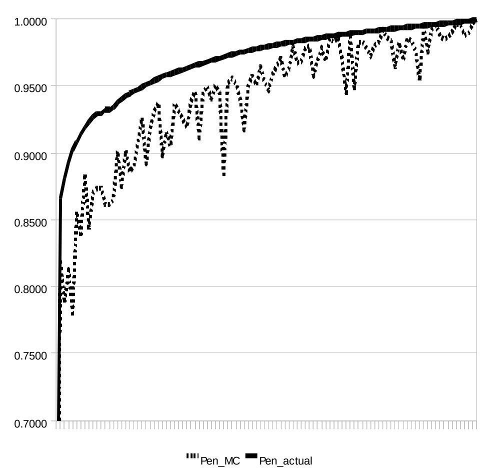


Figure 4.a. - % Welfare change for MC pricing



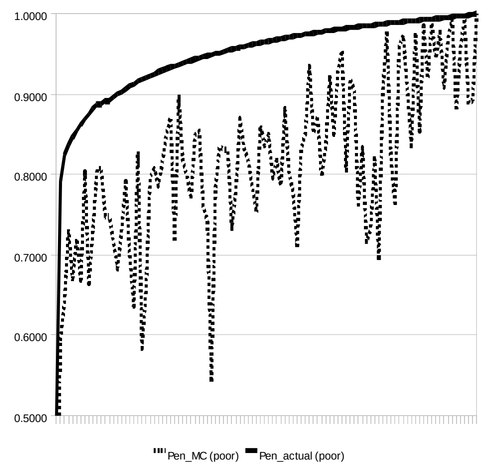
Note: The X-axis represents the % of households in rural areas at the state and the Y-axis represents the % change in welfare at the state.

Figure 4.b. - Actual vs. Experiment Penetration (MC pricing)



Note: The X-axis lists the observation percentiles and the Y-axis represents the actual (Pen_actual) and experiment (Pen_MC) penetration.

Figure 4.c. - Actual vs. Experiment Poor Penetration (MC pricing)



Note: The X-axis lists the observation percentiles and the Y-axis represents the actual (Pen_actual(poor)) and experiment (Pen_MC(poor)) penetration for the poor.

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