Equal Prices, Unequal Access

The Effects of National Pricing in the Life Insurance Industry

Derek Wenning[†]

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Abstract

Regulators that care about financial inclusion may address inequities by restricting price setting. In response, firms may reduce the supply of their product, implying that some households may lose from reduced access. This paper explores this tradeoff in the context of national price setting in the US life insurance industry. I collect a new data set with over one million insurer-agent links across a subset of US commuting zones and document that poor commuting zones have fewer agents per household, fewer active insurers, and smaller and lower-rated insurers relative to rich commuting zones. Motivated by the data, I build a spatial model with multi-region insurers and households with heterogeneous preferences for a differentiated product. The model captures the empirical spatial sorting patterns and admits clear predictions for how insurer location choices change in response to national pricing. I take the model to the data and estimate price elasticities for low- and high-income households. I find that most of the spatial dispersion in welfare under flexible pricing comes from the access margin. National pricing exacerbates spatial disparities due to the geographic reallocation of insurers toward richer markets. Place-based policies that complement national price setting can raise welfare in the life insurance industry by 3.3-5.2% in poor commuting zones and reduce spatial welfare dispersion by 18%.

[†]Princeton University, Department of Economics. Email: dwenning@princeton.edu. I am indebted to my advisors Ezra Oberfield, Motohiro Yogo, and Richard Rogerson for their guidance and support. I also thank Elena Aguilar, David Argente, Markus Brunnermeier, Natalie Cox, Mayara Felix, John Grigsby, Michael Jenuwine, Yuyang Jiang, Moritz Lenel, Hugo Lhuillier, Adrien Matray, David Nagy, George Nikolokaudis, Steve Redding, Wei Xiong, and many other seminar participants for constructive feedback. I am grateful to the Bright Data Inititiative for assistance with data construction.

1 Introduction

Financial regulators often design policies to promote financial inclusion. One such class of policies is price regulation: if regulators feel that prices faced by one group of households are unfair, they may restrict firms' price-setting behavior to protect households from discrimination. This is the motivation behind credit card interest rate caps, for example (Guenette (2020)). However, these policies may have adverse effects if firms respond by limiting the availability of their products. This paper explores this tradeoff in the context of national price setting, a particular type of price control that prohibits geographic price discrimination in the United States life insurance industry. More concretely, how might national pricing affect the availability of life insurance products across geographic markets?

To fix ideas, suppose that low-income households are less price sensitive than high-income households. Consider the case of Metlife, a large life insurer in the United States. Absent regulation, Metlife would optimally set a high price in poor markets like Detroit and a low price in rich markets like New York City. Under national pricing, Metlife's markups, and consequently its profits, fall in Detroit and rise in New York City. Metlife may therefore respond to the policy by reducing their operations in Detroit, perhaps by laying off workers or closing a branch, reallocating their efforts to the relatively profitable New York. Therefore, although Metlife's prices in Detroit are lower, households in Detroit may be less able to access Metlife products at all. The goal of this paper is to quantify the welfare effects of each of these margins.

I set the stage for the paper in Section 2 by examining which locations life insurers choose to enter. Life insurance is a primarily local industry, with over 90% of sales coming from life insurance agents (Insurance Information Institute (2022)). I therefore build a novel data set of over one million insurer-agent links across a sample of US commuting zones, resulting in a comprehensive map of life insurance supply. I use the data to document two stylized facts. First, the poorest quintile of commuting zones have 33% fewer life insurance agents per household and 50% fewer active insurers than the richest quintile. Second, the average insurer in the poorest quintile of commuting zones is smaller and lower rated than the average insurer in the richest quintile. Taken together, the facts point to spatial disparities in life insurance availability in terms of agent accessibility, number of varieties, and insurer quality.

The remainder of this paper explores how these disparities are affected by national pricing regulation. Motivated by the stylized facts, Section 3 outlines a theoretical model with three key ingredients: a set of spatially differentiated locations, households with heterogeneous price elasticities and idiosyncratic tastes over differentiated life insurance varieties, and multi-region life insurers. Insurers hire local sales agents to reach customers. The costs of hiring and managing sales agents depends both on local hiring costs and an insurer's overall size through span of control costs. Taken together, these ingredients generate spatial sorting in a distributional sense: large insurers like Metlife primarily serve large and rich markets, while small insurers like Continental primarily serve small and poor markets.

National pricing has bite when the composition of household types varies across locations. Under flexible pricing, Metlife tailors its prices to the composition of households in each location. But under national pricing, Metlife biases its price toward demand conditions in its most profitable locations. Since Metlife and Continental are active in different types of locations, national pricing generates price dispersion across insurers even in the absence of marginal cost differences: Metlife's prices reflect demand conditions in New York, while Continental's prices reflect demand conditions in Detroit.

Changes in local markups induced by national pricing regulation drive changes in operating profitability, which directly impacts insurers' agent location choices. In locations where Metlife's markups fall (Detroit), it hires fewer local agents and reaches fewer households relative to flexible pricing. Metlife reallocates its activity to locations where its markups rise (New York), hiring more local sales agents and reaching more households.

National pricing therefore generates two competing household welfare effects. Relative to flexible pricing, the average Detroit household benefits from lower prices, but is less likely to be aware of Metlife's products. The price elasticity of a given household determines which effect dominates: price effects matter more for high-elasticity households, while access effects matter more for low-elasticity households. Depending on the extent of spatial agent reallocation, the access effect may reverse the pricing effect, especially for low-elasticity households, leaving them worse off relative to flexible pricing.

Whether or not the access effect dominates for households of each type in each location is ultimately an empirical question. I therefore estimate the model in Section 4. First, I use data on state-level life insurer sales to estimate elasticity differences across households using variation in household type composition across states. The baseline estimation assumes household price elasticities are solely a function of income. I find that low-income households are less price elastic than high-income households, a pattern also found in other financial services such as privatized social security in Hastings et al. (2017). The estimates are robust to using two different instruments and a variety of specifications. I estimate the remainder of the model internally using a combination of model inversion and simulated method of moments. I test the model by predicting agent growth across commuting zones between 2010 and 2022, exploiting variation in population growth across commuting zones. The correlation between the model and the data is 78.1%, suggesting that the model extrapolates well to other settings.

In Section 5, I first use the model to understand which margins drive spatial dispersion in life insurance welfare under flexible price setting. The poorest commuting zones are 50 percent worse off relative to Santa Cruz, the commuting zone with the highest level of welfare. Low-income household welfare drives the difference: welfare is 54 percent lower for low-income households and 27 percent lower for high-income households. Pricing differences only account for 4.4 percentage points of welfare differences for low-income households and 5.8 percentage points of welfare differences for high-income households; differences in access explain the remaining 45.6 percentage points and 21.2 percentage points of welfare differences respectively.

I then impose national pricing in the model and evaluate the welfare effects of the national pricing policy. By design, national pricing eliminates the pricing disparities across commuting zones. However, the effect is offset by the access margin: in response to the policy, insurers reallocate their agents toward high-income commuting zones, exacerbating the access disparities in low-income commuting zones. The effects are strong enough to reverse the pricing gains for low-income households within the poor commuting zones, resulting in welfare losses of around 0.5 percent. Since high-income households are less sensitive to the access margin, high-income households gain in the poor commuting zones by about 0.4 percent. Overall, spatial welfare inequality is amplified for low-income households, but dampened slightly for high-income households.

Motivated by the access consequences of the national pricing policy, I study a complementary and revenue neutral place-based policy designed to target the access margin. The policy reduces tax rates on life insurance premium revenues in the poorest third of commuting zones and finances the loss in tax revenues with tax hikes in the remaining commuting zones. I find that the policy is effective at incentivizing insurer expansion in poor commuting zones: on average, low-income households in the treated commuting zones experience between 2.1-5.3% welfare gains and high-income households experience between 2.3-3.9% welfare gains relative to flexible pricing, depending on the size of the policy. Losses are small for non-treated commuting zones: on average, low-income households in these commuting zones experience welfare losses of around 0.4%, while high-income households in these commuting zones gain by 0.38%.

I evaluate the effectiveness of the policy at the aggregate level in two ways. First, I consider a utilitarian planner that puts uniform welfare weights on all households. Second, I consider a planner whose goal is to minimize spatial inequality in life insurance welfare. Under national pricing alone, utilitarian welfare declines by a modest 0.05% for low-income households and increases by 0.01% for high-income households relative to flexible pricing. Across all households, welfare declines by 0.025%. Further, the spatial variance in welfare increases by about 1%. Incorporating the place-based policy raises utilitarian welfare relative to flexible pricing by 0.15% for low-income households and lowers it by 0.05% for high-income households. But more importantly, the policy decreases the variance in welfare outcomes by about 16% for both high- and low-income households, coming primarily from the large benefits to households in poor commuting zones.

Taken together, the results suggest that access, rather than price discrimination, is the primary disparity in the life insurance industry. While national pricing removes spatial disparities in available prices, it exacerbates the access margin, leaving households worse off in poor locations. Place-based policies, in tandem with national pricing, are effective at targeting the access disparity.

Literature This paper is closest in spirit to the growing literature on uniform pricing. While most papers on uniform pricing focus on retail (DellaVigna and Gentzkow (2019), Aparicio et al. (2021), Butters et al. (2022), Daruich and Kozlowski (2023)), there is also evidence of uniform pricing in other industries like banking (Hurst et al. (2016)), health insurance (Dickstein et al. (2015), Fang and Ko (2020)) and annuities (Finkelstein and Poterba (2004)) which result as a byproduct of government regulation or reputational concerns. The mechanism in this paper is closest to Fang and Ko (2020), who document that health insurers geographically segment within ACA marketplace ratings areas where uniform pricing is enforced. However, they do not discuss the effects on household participation or welfare. In all other work, the literature has entirely focused on the welfare effects of uniform pricing conditional on firms' ex-ante location choices, and do not assess how firms would adjust geographically under uniform pricing relative to a flexible pricing setting. I contribute to this body of literature by taking seriously the location choices of firms and informing how their geographic responses may mitigate or offset the welfare consequences of uniform pricing.

I also contribute to a broader literature on firm responses to price controls. This tradeoff has been studied in several contexts, such as the effects of the minimum wage on hiring dynamics (Pries and Rogerson (2005), Brochu and Green (2011), Kudlyak et al. (2023), among many others), interest rate caps on credit supply and bank branch density (Jambulapati and Stavins (2014), Agarwal et al. (2015), Ferrari et al. (2018), Burga et al. (2023), Nelson (2023)), and many more. I contribute by studying the effect of geographic pricing restrictions and analyzing the effects on firm location choices.

My emphasis on the location decisions of firms also relates to a growing literature on the geographic organization of firms. Several papers have analyzed how firms sort across markets. Gaubert (2018), Ziv (2019), and Lhuillier (2023) focus on single-establishment firms, while Oberfield et al. (2023a) and Kleinman (2023) focus on multi-establishment firms. Oberfield et al. (2023b) builds on Oberfield et al. (2023a) by looking at how multi-region bank sorting changed following geographic deregulation. This paper contributes by examining how pricing frictions affect spatial sorting and location decisions, highlighting that sorting may also be a byproduct of regulation.

The link between spatial sorting and pricing is one margin absent from the literature on life insurance pricing. Many papers point to financial frictions being an important driver of insurance prices, e.g. Koijen and Yogo (2015), Koijen and Yogo (2016), and Ge (2022). I document that life insurance prices may also be sensitive to the geographic distribution of insurer activity. This channel is strong as well, explaining a large fraction of cross-sectional variation in prices across insurers.

Finally, I contribute to the literature on financial inclusion. Local financial services are important for understanding differences in financial participation, such as bank branch density (Célerier and Matray (2019)) or access to retirement accounts through local firms (Yogo et al. (2023)). Many developing countries also feature alternative forms of financial access such as mobile banking (Agarwal et al. (2017), Ouyang (2023), Brunnermeier et al. (2023)). The mobile banking literature emphasizes the importance of geography as well, with households out of range of mobile towers unable to participate. Brunnermeier et al. (2023) specifically show that encouraging competition through regulation reduces the supply of mobile towers in underserved locations. This paper combines local services with pricing regulation in a structural model that gives similar findings.

2 Geography and Pricing in the Life Insurance Industry

This section describes the institutional details of the life insurance industry. First, I discuss the institutional setting and why regulators impose national pricing restrictions. I then discuss the data sets I use and document three key facts about the geography of the life insurance industry and the relationship between life insurance pricing and insurer location decisions.

2.1 Institutional Setting

2.1.1 Price Discrimination and National Pricing Regulation

Life insurers must demonstrate to regulators that their products only reflect the operating costs of the company and the mortality risk of their customers. Prices are allowed to vary by factors directly related to mortality risk, such as age: older people have higher short-term mortality risk than young people, so premiums are increasing in the age of the insured. Health status, gender, occupation, and smoking patterns are also used to price life insurance.[1]

Anti-discrimination laws set by the National Association of Insurance Companies (NAIC), the regulatory body for US insurance companies, prevent further discrimination along protected factors such as race, marriage status, or religion. At the neighborhood level, race in particular is strongly correlated with factors that may be desirable to price, such as income, crime, or pollution.[2] These geographic factors may therefore be viewed as proxies for racial composition, and are therefore prohibited. Life insurance prices are therefore required to be set at the national level.

Life insurers could theoretically discriminate against households along other margins. For example, Metlife could offer two seemingly identical products that only differ by the legal identification of the product and in the premium rate. Regulators anticipate this behavior and have also imposed strict guidelines on the creation of new products. Metlife must demonstrate that price differences across their products are actuarially sound and reflect well-defined costs and mortality risk; given

[1]Insurance companies may also collect credit scores, but they are only allowed to set prices based on a household's previous bankruptcy status. This is motivating by findings that households that file bankruptcy are more risky in the sense that they are less likely to repay their premiums.

[2]The correlation coefficient between per-capita income and non-white household share is -38% at the census tract level using the 2016-2020 wave of the American Community Survey. For crime, see Lodge et al. (2021). For pollution, see Jbaily et al. (2022) and Currie et al. (2023).

an existing approved product, Metlife is not permitted to create near-replicas of the product. Regulators also enforce that every agent licensed by a company must offer the full menu of products, further limiting the ability to price discriminate through product differentiation.

A life insurer may also attempt to price discriminate through its organizational structure. Life insurance companies are often a part of a group, the insurance equivalent of a holding company. A group could theoretically consist of multiple life insurance subsidiaries that serve distinct geographic markets and set prices that reflect their respective local demand conditions. However, this type of organization would likely be prohibitively costly for insurance groups due to regulatory frictions in capital requirements and costly internal capital transfers between subsidiaries. Statutory capital regulation requires that each insurance company within a group be adequately diversified. By concentrating in economically similar regions, a subsidiary is more exposed to idiosyncratic regional mortality risk, pushing them closer to their statutory capital constraints. These constraints, along with the fixed costs of creating and managing distinct companies, would likely outweigh the benefits of geographic price discrimination.[3]

2.1.2 *The Role of Insurance Agents in Product Distribution*

As with many forms of insurance, life insurance is primarily sold through local life insurance agents. According to the Insurance Information Institute, 90% of life insurance premiums in 2022 were generated through life insurance agents, with only 6% coming from purely direct sales through online platforms with no agents involved (Insurance Information Institute (2022)). According to the Life Insurance Marketing and Research Association (LIMRA), while some households choose to learn about products online, the majority ultimately purchase insurance through an agent (LIMRA (2022)).

Life insurance sales are predominantly local. Although many agents are licensed to sell products in multiple states, Bhattacharya et al. (2020) document that 60% of sales come from within the county an agent is located in. This share grows even more when expanding to neighboring counties. The authors further document a very small share of sales coming from distant transactions. Motivated by their findings, I use the commuting zone as my geographic unit of analysis and interpret local agent availability as a proxy for life insurance accessibility.

Survey evidence also points to local agent supply as a factor preventing households from obtaining life insurance. According to LIMRA (2022), of the households that do not own life insurance, 35% report that they simply have not been approached by an agent. 52% also report uncertainty about the type and amount of life insurance to buy, information that agents specialize in. Both of

[3] In Appendix D.1, I test for the possibility of within-group price discrimination by regressing company-level prices on a company and a group fixed effect. In all specifications, 80-90% of the explained variation in prices are attributed to the group fixed effect. This implies that even if groups do discriminate through disaggregation, the effects are not strong. This is further justified by the fact that most companies within an insurance group have significant geographic overlap, which I also document in Appendix D.1.

these facts speak to agent supply as being an important driver of life insurance ownership. This is echoed in a report by Casparus Kromhout, the CEO of Shriram Life Insurance Company, on the Indian economy Kromhout (2023). The report emphasizes that agent supply disparities are a key reason for the rural-urban gap in life insurance coverage.

2.2 Data Construction

Life Insurance Agents Life insurance agent information is from the National Association of Insurance Commissioners State-Based Systems (NAIC-SBS). The NAIC-SBS data provide a snapshot of the agents licensed at the time of data collection. At the time of data collection in August 2022, 28 states had opted in to NAIC-SBS, 18 of which provide detailed information about each agent.[4] The data provide a full mapping of life insurers to agents operating in the states available. Importantly, the data include information on agents' business locations at the zip code level which I match to 1990 commuting zones.

Financial Statements Life insurer balance sheet data are from A.M. Best Financial Suite (AMB) from 2007-2019. I use data on liabilities, leverage, financial ratings, return on equity, organizational structure, and state-level life insurance premiums.

Life Insurance Prices Life insurance premiums are from Compulife, a quotation software used by life insurance agents. I pull data for 10-, 20-, and 30-year term life insurance products from 2007-2018 that pay out \$250,000 upon the death of the insured. I focus on non-smoking males and females aged 30-50 (in 10-year increments) in the regular health category.

Life insurance premiums vary substantially across maturity lengths, age groups, and gender due to differences in expected returns and mortality rates. I follow Koijen and Yogo (2016) and normalize the premiums by the actuarially fair value for each product, which takes the form

$$v^{agm} = \left(1 + \sum_{k=1}^{m-1} R^{-k}(k) \prod_{\ell}^{k-1} \rho_{a+\ell}^{g}\right)^{-1} \left(\sum_{k=2}^{m} R^{-k}(k) \prod_{\ell=0}^{k-2} \rho_{a+\ell}^{g}(1 - \rho_{a+k-1}^{g})\right) \tag{1}$$

where $\rho_{a+\ell}^{g}$ is the survival probability conditional on a 5% lapsation rate for an individual at age $a+\ell$ and gender g, and $R(k)$ is the zero-coupon Treasury yield at maturity k.[5] Survival probabilities

[4]The states available are AL, AR, CT, IA, MA, MT, NC, ND, NE, NH, NJ, NM, OK, SC, TN, VT, WI, and WV. Delaware also provides agent-insurer links, but 90% of their agents are listed as inactive. Delaware is a relatively small state, and their active agents totalled only 0.05% of the sample, so I exclude Delaware from the analysis. See Appendix Table C.1 for more details about the data.

[5]I choose a 5% lapsation rate based on the national average lapsation rate in 2018. This measure is consistent if lapsation rates do not differ across firms. I run all subsequent analysis with an assumed lapsation rate of 0% and find similar results.

are taken from the 2015 Valuation Basic Table provided by the American Society of Actuaries.[6] Treasury yields are taken from the zero-coupon Treasury yield curve in June of each year, the same month as the reported life insurance quotes. I define the price of an insurance product p_j^{amg} as its premium rate divided by the fair value, (1).

Market Characteristics I use household populations, high-income population shares, and demographics from the 2016-2020 American Community Survey five-year estimates (ACS). I define a high-income household as one whose income is above the 2020 national median income, $75,000.

Summary Statistics The NAIC-SBS sample includes 211,203 local agents operating in 280 commuting zones and representing 438 life insurers. This sample of life insurers accounts for 97.6% of the life insurance industry by premiums, and the premiums of these life insurers in the states in my sample make up 23% of all life insurance premiums in the United States.

The Compulife pricing data contain only 70 of the 438 insurance companies in the NAIC-SBS sample. Longer maturity products have fewer insurers, with 68 insurers offering 10-year term life products and 55 insurers offering 30-year term life products. The insurers in the Compulife sample are relatively large: of the insurers in the NAIC-SBS sample, the Compulife insurers account for 44% of all agents, 53.6% of premiums, and 41.3% of liabilities.

The average price across categories is 1.00, the minimum is 0.47, and the maximum is 3.02.[7] Note that prices below 1 do not necessarily imply that insurers are losing money on these products. Many policies lapse, which is equivalent to a premature termination of the product and acts as a windfall of profits to the insurer. The fair value I compute in equation (1) only takes into account average lapsation rates, and does not include variation in lapsation probabilities across age groups and maturity lengths. However, as long as the lapsation mismeasurement is stable in the cross section of firms and product categories, this should not affect subsequent estimates.[8]

2.3 Stylized Facts

This section highlights three stylized facts that I incorporate into the model. The first fact focuses on the geographic allocation of insurers and agents across commuting zones. The second fact documents spatial sorting patterns. Finally, the third fact documents the relationship between insurers' prices and their geographic footprints.

[6] These probabilities are computed from insured pools, and therefore account for adverse selection.

[7] See Appendix Table C.2 for a more detailed breakdown of the pricing data.

[8] I perform a sensitivity analysis with respect to the assumed lapsation rate in Appendix D.3. The results are nearly identical to the baseline lapsation assumption of 5%.

Table 1: Agents in the Cross Section of Commuting Zones

		CZ High-Income Share Quintile				
Average...	All CZs	1	2	3	4	5
Number of Insurers	135	97	127	135	159	176
Number of Agents	754	146	333	424	930	2349
Agent Density	6.30	4.73	6.06	6.90	7.50	7.00
Insurers Per Agent	4.15	3.25	3.94	4.45	4.52	5.04

Note: This table reports summary statistics about the life insurance across US commuting zones. The CZ high-income share quintile is calculated based on the commuting zones in the NAIC-SBS sample. Agent density is defined as the number of agents per thousand households in a commuting zone.

Fact 1: Poor Commuting Zones Have Fewer Life Insurance Options than Rich Commuting Zones

As I highlight in Section 2.1, life insurance is predominantly accessed locally. To what extent are life insurance services available across commuting zones? Do poor places have the same access to life insurance as rich places?

Table 1 documents variation in agent and insurer availability across commuting zones. On average, there are about 786 licensed agents and 138 insurance companies licensing at least one agent in a commuting zone. The richest quintile of commuting zones have on average nearly twice the number of active insurers and 16 times the number of licensed agents relative to the poorest quintile of commuting zones. These differences persist even after controlling for household population: the richest commuting zones have on average 48% more agents per household relative to the poorest commuting zones.

Households may also learn about different insurer varieties after matching with a life insurance agent if the agent offers products from multiple companies. In the poorest quintile of commuting zones, the average agent offers products from 3.25 different insurance companies. In the richest quintile, the average agent offers products from 5.04 different companies, 55% more than the poorest quintile. Taken together, the data suggest large disparities across commuting zones in terms of accessing life insurance services through agents, as well as disparities in the varieties available both unconditionally and conditional on matching with an agent.

Fact 2: Large Insurers Are Biased Toward Denser and Richer Commuting Zones

Fact 1 emphasized differences in life insurance supply across commuting zones. But life insurers have characteristics that may be more or less desirable, e.g. their financial rating or outstanding leverage, which implies a relevant quality dimension to local life insurance supply. Are there systematic differences in which insurers are available across geographic markets? More concretely, do large firms like Metlife disproportionately license agents in large or rich markets relative to small firms like Continental?

I test for the presence of sorting by estimating the following regression:

$$\log(\text{agents}_{j,cz}) = \beta^X_{\text{inc}} \log(\text{income}_{cz}) \times X_j + \beta^X_{\text{pd}} \log(\text{density}_{cz}) \times X_j + \gamma_j + \gamma_{cz} + u_{js} \tag{2}$$

I interpret positive β^X_m coefficients as evidence for sorting along their respective margins m. In this regression, income_{cz} is the share of high-income households in commuting zone cz and density_{cz} is the household population density of commuting zone cz. The firm-level variable X_j is either the log of firm j's liabilities — a measure of insurer size — or their financial rating converted to a numerical scale following A.M. Best Company (2016) — a measure of insurer quality. I standardize each independent variable.

Note that many agents in the NAIC-SBS data are licensed to sell the products of multiple firms: 38.2% of the agents in my sample are licensed to sell products from a single insurer, 46.7% are licensed to sell products for 2-10 insurers, and the remaining 15.1% are licensed to sell more than 10. I therefore consider a fractional measure of agents that accounts for within-agent competition. For example, if an agent sells both Metlife and Continental products, I assign each insurer a value of 1/2 for that agent. The measure $\text{agents}_{j,cz}$ is the sum of firm j's fractional agents in commuting zone cz.

For insurer size, I estimate $\beta^{\text{size}}_{\text{inc}} = 0.128$ and $\beta^{\text{size}}_{\text{pd}} = 0.238$ with t-statistics 17.95 and 28.37 respectively. For insurer quality, I estimate $\beta^{\text{qual}}_{\text{inc}} = 0.109$ and $\beta^{\text{qual}}_{\text{pd}} = 0.123$ with t-statistics 14.04 and 13.63, respectively. These estimates imply that richer and denser commuting zones have a greater share of large and high-quality insurers relative to poorer, rural commuting zones. Therefore, beyond having access to fewer life insurance varieties, low-income commuting zones may have lower access to higher quality and more established insurance companies and products relative to high-income commuting zones.

Fact 3: Prices Reflect Differences in Local Household Characteristics

Despite national pricing regulation, insurers may still have motives to price discriminate based on the characteristics of households in their active markets. Having established that insurers sort into different types of markets, I test whether the observed sorting differences matter for insurance prices.

I begin by documenting correlations between prices and average geographic characteristics of insurers' agents' locations. The variables of interest are the average share of high-income households, average share of non-white households, and population density of each insurer's active commuting zones weighted by the distribution of their fractional agents. I subsequently add firm characteristics and proxies for local competition into the analysis to account for differences in costs and market power, which could also explain price differences across insurers. With all of the controls accounted for, the regression specification is

$$\log(p_j^{am}) = \theta_{\text{inc}}\overline{\log(\text{income}_j)} + \theta_{\text{nw}}\overline{\log(\text{non-white}_j)} + \theta_{\text{pd}}\overline{\log(\text{density}_j)} + \boldsymbol{\theta}_f'\boldsymbol{X}_j^f + \boldsymbol{\theta}_c'\boldsymbol{X}_j^c + \gamma_{am} + \epsilon_{jam} \quad (3)$$

The price p_j^{am} is firm j's premium rate divided by actuarial value for households of age a and maturity m averaged across gender groups. Firm characteristics $\boldsymbol{X}_j^f$ include variables commonly associated with other aspects of life insurance demand and insurer costs. I include log liabilities (size), leverage, financial rating, return on equity, and an indicator for whether firm j is a stock company. The local competition proxies $\boldsymbol{X}_j^c$ account for local market power and agent incentives across an insurer's active markets. The first variable is the average fractional agent for each insurer. An independent agent that sells products for multiple insurers may have incentives to push more expensive products on customers since they would receive a higher commission, incentivizing insurers to set higher prices. Conversely, insurers that use captive agents may set lower prices since they do not have to compete with other insurers after their agent matches with a household. The second variable is the average market share of an insurer's fractional agents which captures average local market power across insurers. I cluster standard errors at the insurer level.

Table 2 displays the results. Column (1) only includes geographic variables, column (2) adds in firm characteristics, and column (3) adds in the competition proxies. I standardize all independent variables. For brevity, I only report the estimates for the geographic variables since they are the point of interest. Table C.3 in the appendix provides the full set of results.

Local income is consistently negatively associated with prices and is significant at the 1%, 10% and 5% levels across specifications, respectively. The negative correlation potentially reflects stronger price sensitivity for high-income households. This interpretation is in line with other work on financial services, e.g. privatized social security in Hastings et al. (2017), that attribute the relatively low price sensitivity of low-income households to differences in financial literacy. If high-income households are more financially literate, then they may be more inclined to shop around the for the cheapest policy. Low-income households may instead take the advice of their life insurance agent without question, trusting that the agent's knowledge is greater than their own.

Non-white share is consistently positively associated with prices and is always significant at the 1% level. This relationship could reflect three things. First, it could imply that non-white households are less price elastic than white households. Second, it could reflect differences in mortality rates across racial groups. However, since insurers are required to use aggregate mortality tables when calculating prices, this seems unlikely to be the case. Third, it could reflect explicit discrimination.

Density is consistently insignificantly related to prices, suggesting that differences in prices are reflecting differences in local household characteristics rather than local costs. If dense commuting zones lead to agglomeration effects for insurers as they do in other industries, then we might expect

Table 2: The Determinants of Cross-Sectional Price Dispersion

	(1)	(2)	(3)
Income	−0.117	−0.083	−0.096
	(0.038)	(0.046)	(0.047)
Non-White	0.081	0.089	0.101
	(0.024)	(0.026)	(0.027)
Density	0.009	−0.014	−0.017
	(0.047)	(0.052)	(0.055)
Firm Controls		✓	✓
Competition Controls			✓
Age × Maturity Fixed Effects	✓	✓	✓
Observations	746	746	746
Within R^2	0.32	0.35	0.37
% of Explained Variation:			
Income	61.2	20.9	15.7
Non-White	38.5	50.2	41.5
Density	0.3	3.8	4.3
Other Controls	—	25.1	38.5

Note: This figure reports the regression results for equation (3). The independent variable is the log premium for an individual of age a and product maturity m normalized by the fair value. Income is the agent-weighted share of high-income households, Non-White is the agent-weighted share of non-white households, and Density is agent-weighted log density. Firm controls include log liabilities, leverage, financial rating, return on equity, and an indicator for stock companies. Competition controls include average fractional agents and average local agent market share. Standard errors are clustered by company and reported in parentheses.

a significant negative relationship. The estimates do not support this notion.

I perform a variance decomposition of equation (3) to understand which variables are the most important for price differences across insurers. I calculate the implied sum of squared variation coming from each of the variables, then calculate the share of variation for each variable out of the total explained variation. The results are reported in the bottom of Table 2. Non-white household share and local income consistently explain the majority of the variation in prices, with density being relatively unimportant. This result emphasizes that geographic variation in insurers' active markets is an important factor for understanding cross-sectional price dispersion and points to potential price discrimination motives in the industry.

Recap of the Facts

The stylized facts suggest that (1) low income commuting zones have fewer agents and insurers relative to high-income commuting zones, (2) insurers in low-income commuting zones are on average smaller and lower quality than insurers in high-income commuting zones, and (3) life insurance prices correlate strongly with local household characteristics, suggesting a motive for price discrimination. The next section builds a theoretical framework that incorporates Facts 1-3.

3 A Spatial Model of Life Insurance Distribution

The forthcoming model is designed to rationalize stylized Facts 1 (spatial disparities in supply) and 2 (spatial disparities in quality). Fact 3 (spatially-biased pricing) emerges as a consequence of Fact 2. I start with an otherwise standard model of monopolistic insurers that tailor prices to local demand conditions. I enrich the model with two additional costs that, with enough structure, generate spatial sorting patterns in line with the data. I then demonstrate how pricing frictions interact with insurer location choices and highlight how these interactions affect household welfare.

3.1 Model Setup

Fundamentals There is a large number of monopolistically competitive insurers indexed by $j \in \mathcal{J}$, each producing a differentiated variety. The total number of insurers is $J = |\mathcal{J}|$. There is a finite set of locations $s \in \mathcal{S}$ endowed with a mass of households N_s. Within each location s, there are two types of households, $k \in \{\ell, h\}$, with population shares η_s^k and expenditure shares χ_s^k.[9] In the quantification, I assume that types are perfectly correlated with household income.

Insurers An insurer reaches households in a location by hiring agents, a_{js}, which market the insurer's product to local households. Insurers are heterogeneous in their efficiency at reaching local households, θ_j. I refer to θ_j as j's productivity. The probability that a given household in location s includes insurer j's product in its choice set is $\kappa(a_{js}, \theta_j, N_s)$, which I refer to as insurer j's market penetration in s. Market penetration is increasing and concave in the insurer j's agents, a_{js}, increasing in j's productivity, θ_j, and decreasing in the size of market s, N_s. For brevity, I use the shorthand $\kappa_{js}(a_{js}) \equiv \kappa(a_{js}, \theta_j, N_s)$. In the quantitative extension of the model, I use the functional form

$$\kappa_{js}(a_{js}) = 1 - \exp\Big(- \theta_j a_{js}/N_s^{\alpha}\Big). \tag{4}$$

[9] I assume only two types for expositional simplicity and to map the model the data for estimation. I show in Appendix B.1 how to extend the framework to a continuum of types.

Arkolakis (2010) provides an explicit microfoundation for (4), which I explain in Appendix B.2. The parameter α governs the strength of the market size penalty. When $\alpha = 0$, a given mass of agents a reaches the same fraction of households in small markets like Frankfurt, KY and large markets like New York City. As α increases, an insurer needs more agents to reach the same fraction of households in larger markets.

Insurers face a constant marginal cost $\xi > 0$ for each unit of the good they produce. In the life insurance industry, marginal costs come from the generation of insurance policies. These costs may include commissions paid to agents, underwriting costs, premium taxes, or regulatory and financial frictions. I hold marginal costs constant across insurers throughout the theory for simplicity, but allow for insurer-level marginal cost heterogeneity when I estimate the model.

Insurers must also pay local hiring costs f_s for each agent they hire. Since life insurance agents are generally compensated through commissions, I interpret these costs as search and licensing costs. This assumption is reasonable due to the high turnover rate of insurance agents: on average, 90% of agents quit within their first three years (A.M. Best Company (2021)). Insurers may therefore incur significant hiring costs over short time periods as they consistently rebuild their agent base. In the quantification, I capture the potential increasing costs of hiring volume by assuming f_s is a function of market size and market income, $f_s \equiv f(\eta_s^h, N_s)$.

Last, insurers incur span of control costs $C(\bar{a}_j, \theta_j)$, where $\bar{a}_j$ is the total mass of agents licensed by insurer j across its active locations. These costs reflect the managerial capacity of insurers. I assume $C(\cdot, \theta_j)$ is increasing, strictly convex, and is equal to 0 if $\bar{a}_j = 0$. I write $C_j(\bar{a}_j) \equiv C(\bar{a}_j, \theta_j)$ when convenient.

Hiring costs and span of control costs are important ingredients for the model to generate realistic spatial sorting patterns. When hiring costs are identical across regions, every insurer will be active in the most profitable markets since high-volume locations will always allow them to overcome local costs. As I showed in Section 2.3, this is not the case for life insurance: small life insurers are disproportionately present in small markets relative to large insurers. Conversely, span of control costs control which insurers enter the small markets. When span of control costs are small, large insurers will always be more active in smaller markets than small insurers, which is also not the case in the data. I demonstrate this intuition formally in Section 3.3.

Given a mass of licensed agents a_{js} and price p_{js}, insurer j's variable profits in location s can be written

$$\pi_{js}(p_{js}, a_{js}) = (p_{js} - \xi) \sum_k Q_s^k\Big(p_{js}, \kappa_{js}(a_{js}), P_s^k\Big) - f_s a_{js} \tag{5}$$

where $\{Q_s^k(\cdot)\}_k$ are residual demand curves for type k households. The residual demand curves are the result of households' discrete choices, which I outline in the next section. Under monopolistic competition with a large number of insurers, insurers choose the price of their variety taking the price indices as given. The set of prices chosen by an insurer are restricted to be in a given set $\mathcal{P}$. I refer to $\mathcal{P}$ as the regulatory regime, which can either be flexible pricing ($\mathcal{P}^{\text{flex}}$) or national pricing ($\mathcal{P}^{\text{natl}}$).

Insurer j's problem is to choose a vector of agents $\mathbf{a}_j$ and a vector of prices $\mathbf{p}_j$ to maximize its total profits subject to the regulatory regime $\mathcal{P}$:

$$\Pi_j(\mathcal{P}) = \max_{\mathbf{a}_j, \mathbf{p}_j} \left\{ \sum_{s \in \mathcal{S}} \pi_{js}(p_{js}, a_{js}) - C(\bar{a}_j, \theta_j) \;\middle|\; \begin{array}{l} \mathbf{a}_j \geq 0 \\ \mathbf{p}_j \in \mathcal{P} \end{array} \right\}. \tag{6}$$

Demand Households make a discrete choice over available insurance products. Household-level choice sets, $\mathcal{J}_{is} \subset \mathcal{J}$, are a random variable: a given household i in location s is aware of insurer j with probability κ_{js}. Households may also choose to consume an outside option o, which I assume is always available for all households and locations and is provided at a price $p_o = 1$.[10] Household i of type $k(i)$ in location s values insurer j according to

$$u_{ijs} = \log \iota_{k(i)} - (\varepsilon_{k(i)} - 1) \log p_{js} + \nu_{ij} \tag{7}$$

where $\iota_{k(i)}$ is the value of being insured relative to the outside option for households of type $k(i)$ and ν_{ij} is an idiosyncratic taste shock over the set of available insurers and outside options and is distributed according to an Extreme Value Type I distribution with zero mean and unit variance. I assume price elasticities ε_k are heterogeneous across household types, $\varepsilon_h > \varepsilon_\ell$, and I impose the restriction $\varepsilon_k > 1$ for each k. In the quantification, I also allow preferences to depend on a vector of insurer characteristics to account for differences in insurer quality. This is an important additional channel for understanding how insurer sorting patterns affect equilibrium household welfare.

Price elasticity heterogeneity may capture several aspects of household preferences. For example, high-income households may have stronger preferences for leaving bequests. Bequest motives boost households' effective discount factors and increases the value of life insurance, therefore increasing their price sensitivity to life insurance products. I microfound this bequest motive in Appendix B.4 and show that indirect utility takes the same form as (7). Price elasticities may also capture differences in financial literacy (Hastings et al. (2017)), search costs (Hortaçsu and Syverson (2004)), or non-homotheticities (Handbury (2021)). I do not take a stand on which channel is active, and instead take the price elasticities as given and infer them from the data in Section 4.

A household's problem is to choose $j \in \mathcal{J}_{is} \cup \{o\}$ to maximize u_{ijs}. The solution to this optimization problem implies type-specific residual demand curves facing insurer j in market s,

[10] A unit price can be rationalized if the outside option is defined as an alternative savings instrument that is priced at fair value such as a government bond. Appendix B.3 shows how to define the problem with this microfoundation. In this case, insurer prices can be interpreted as markups over the actuarially fair value.

$$Q^k_{js}\Big(p_{js},\kappa_{js},P^k_s\Big)=\iota_k\left(\frac{p_{js}}{P^k_s}\right)^{1-\varepsilon_k}\frac{E^k_s\kappa_{js}}{p_{js}},\qquad P^k_s=\left(1+\iota_k\int_{\mathcal{J}}\kappa_{js}p_{js}^{1-\varepsilon_k}dj\right)^{\frac{1}{1-\varepsilon_k}}\tag{8}$$

where $E^k_s=\beta w_k\eta^k_s N_s$ are total expenditures by type k households across varieties in market s, β is the aggregate share of income dedicated to life insurance, and w_k is the average wage of type k households. With preferences as in (7), the average welfare of a type k household in location s is w_k/P^k_s. Note that the market-type price index P^k_s depends on both the distribution of prices $\{p_{js}\}_{j\in\mathcal{J}}$ and the distribution of market penetration $\{\kappa_{js}\}_{j\in\mathcal{J}}$ across insurers which implies a welfare margin associated with insurers' local operating intensity. Under the assumption of random meetings, κ_{js} is equivalently the share of local households that consider j in their choice set. If Metlife hires more agents in location s, then a higher share of households will include Metlife in their choice set, inducing a love of variety effect.

Equilibrium I treat the life insurance industry as small relative to the economy and therefore take household fundamentals $\{N_s,\{\eta^k_s\}\}_{s\in\mathcal{S}}$ and $\{w_k\}_{k=\ell,h}$ as given. I also take local hiring costs $\{f_s\}$ as given, though I outline an extension that endogenizes hiring costs in Appendix B.6. A formal definition of the model equilibrium is as follows.

Definition 1: Industry Equilibrium

Given local fundamentals $\{N_s,\eta_s,f_s\}_{s\in\mathcal{S}}$, household fundamentals $\{\varepsilon_k,w_k\}_{k=\ell,h}$, and regulatory regime $\mathcal{P}$, an industry equilibrium is such that

1. *Households make discrete choices over products consistent with utility maximization*
2. *Insurers maximize profits taking price indices $\{P^\ell_s,P^h_s\}_{s\in\mathcal{S}}$ as given*
3. *Local price indices are consistent with insurers' optimal choices $\{\mathbf{a}_j,\mathbf{p}_j\}_j$*

In Appendix B.7, I also consider a setting in which there are a small number of insurers and allow insurers to internalize how their price and agent decisions affect local price indices. As the number of insurers grows, the two equilibria coincide, so I only consider the monopolistically competitive market structure for the remainder of the theory.

3.2 Optimal Price Setting

This section analyzes how insurers set prices across the two regulatory regimes. Before doing so, it will be helpful to describe some notation. Let $S^k_{js}\equiv p_{js}Q^k_{js}$ be insurer j's sales to type k households in market s, and define the shares

$$\delta_{js}^{\mathrm{w}k} = \frac{S_{js}^k}{\sum_{k'} S_{js}^{k'}}, \qquad \delta_{js}^{\mathrm{b}} = \frac{\sum_k S_{js}^k}{\sum_{s'} \sum_k S_{js'}^k}. \tag{9}$$

$\delta_{js}^{\mathrm{w}k}$ is the share of insurer j's sales in location s that come from type k households. I refer to this as the within-market-type sales share of insurer j. δ_{js}^{b} is insurer j's sales share between markets and types. With these definitions in place, the following proposition characterizes an insurer's optimal price for a given regulatory regime $\mathcal{P}$.

Proposition 1: Optimal Price Setting

Insurer j's optimal price is given by

$$p_{js} = \left(\frac{\zeta_{js}(\mathcal{P})}{\zeta_{js}(\mathcal{P}) - 1}\right)\xi, \qquad \zeta_{js}(\mathcal{P}) \equiv \begin{cases} \sum_k \delta_{js}^{\mathrm{w}k}\varepsilon_k, & \text{if } \mathcal{P} = \mathcal{P}^{\mathrm{flex}} \\ \sum_{s' \in \mathcal{S}} \delta_{js'}^{\mathrm{b}} \sum_k \delta_{js'}^{\mathrm{w}k}\varepsilon_k, & \text{if } \mathcal{P} = \mathcal{P}^{\mathrm{unif}} \end{cases} \tag{10}$$

Proof: See Appendix A.1.

This result is standard in the uniform pricing literature. Absent pricing restrictions, prices are tailored to the elasticity of the dominant household type in a given location. I refer to this elasticity as the local elasticity of demand. Under national pricing, an insurer's price reflects local elasticities across all of its active markets, with the most weight put on the locations in which it receives the most sales.

Proposition 1 shows why accounting for spatial sorting patterns is important for understanding dispersion in prices under national pricing beyond differences in insurer characteristics and competition discussed in Section 2.3. Sorting is reflected in differences in the spatial sales distributions across insurers, $\{\boldsymbol{\delta}_j^{\mathrm{b}}\}_j$. If Metlife locates in high-type markets relatively more than Continental, then $\zeta_{js}^{\mathrm{Metlife}} > \zeta_{js}^{\mathrm{Continental}}$, implying that Metlife sets a lower markup than Continental. The next section details how these spatial sorting patterns are determined.

3.3 The Determinants of Spatial Sorting

Insurers trade off the costs of adding agents in a location with the increase in revenues that the agents would bring. Define the local profitability of insurer j in location s as

$$\Phi_{js}(p_{js}) = (p_{js} - \xi) \sum_{k=\ell,h} \iota_k \left(\frac{p_{js}}{P_s^k}\right)^{1-\varepsilon_k} \frac{E_s^k}{p_{js}}. \tag{11}$$

The mass of agents hired by insurer j in location s is determined by the optimality condition

$$\underbrace{\Phi_{js}(p_{js})\kappa'_{js}(a_{js})}_{\substack{\text{profitability of}\\ \text{the marginal agent}}} \leq \underbrace{f_s + C'_j(\bar{a}_j)}_{\substack{\text{costs of}\\ \text{the marginal agent}}} \quad . \tag{12}$$

The insurer sets $a_{js} = 0$ when $\Phi_s(p_{js})\kappa'_{js}(0) < f_s + C'_j(\bar{a}_j)$, which may be the case given the functional form (4) used in the quantitative section. This condition features a typical cost-benefit tradeoff for insurer j. If j increases its number of agents in market s, it earns profits $\Phi_s(p_{js})$ times the change in the share of households reached, $\kappa'_{js}(a_{js})$. On the cost side, the insurer incurs additional hiring costs f_s for the marginal agent and incurs a higher span of control cost, $C'_j(\bar{a}_j)$. The span of control term can be viewed as an opportunity cost: if Metlife adds an agent in Trenton, any additional agents in New York will be increasingly costly to manage. Metlife therefore internalizes how operating in one market affects its operations in all other markets.

How does productivity affect how insurers place agents across markets? In order to characterize the agent location decisions, I impose the following structure on insurers' technology:

Assumption 1: Insurer Technology Structure

Define a insurer's local efficiency units as $A_{js} \equiv \theta_j a_{js}$, *and let* $\bar{A}_j \equiv \sum_s A_{js}$. *Span of control costs and market penetration can be written as*

$$C(\bar{a}_j, \theta_j) = \widetilde{C}(\bar{A}_j), \qquad \kappa(a_{js}, \theta_j, N_s) = \tilde{\kappa}(A_{js}, N_s)$$

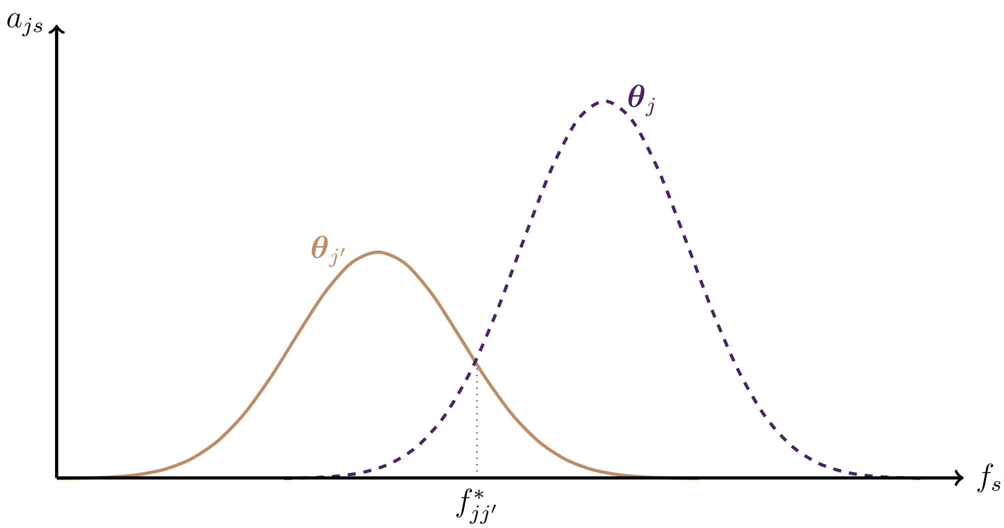
where $\widetilde{C} : \mathbb{R}_+ \to \mathbb{R}_+$ *is increasing and strictly convex and* $\tilde{\kappa} : \mathbb{R}^2_+ \to [0,1]$ *is increasing and strictly concave in the first argument and decreasing in the second argument.*

Assumption 1 implies that market penetration and span of control costs are a function of efficiency units, $A_{js} \equiv \theta_j a_{js}$, rather than raw agents. Though the span of control assumption is primarily technical, it can also be justified if advertising expenditures and organization are correlated with agent marketing efficiency. If Metlife devotes a larger amount of management time to advertising strategy, they have less managerial resources to devote to monitoring and training their agents. As a result, they face stronger span of control costs than Continental, who may not invest as much time in advertising. Under this assumption, I prove the following result.

Proposition 2: Single-Crossing Condition

Suppose $\theta_j > \theta_{j'}$ *and suppose Assumption 1 holds. Then for each pricing regime* $\mathcal{P}$, *there exists a unique* $f^*_{jj'}(\mathcal{P})$ *such that* $A_{js}(\mathcal{P}) > A_{j's}(\mathcal{P})$ *when* $f_s > f^*_{jj'}(\mathcal{P})$ *and* $A_{js}(\mathcal{P}) < A_{j's}(\mathcal{P})$ *when* $f_s < f^*_{jj'}(\mathcal{P})$.

Figure 1: The Single-Crossing Property



Note: This figure displays the single-crossing property for two insurers with $\boldsymbol{\theta}_j > \boldsymbol{\theta}_{j'}$. The cutoff $f^*_{jj'}$ marks the point at which the two insurers operate with the same number of efficiency units.

Proof: See Appendix A.2.

Proposition 2 is a result about spatial sorting. We can think of the inefficient insurer as Continental and the efficient insurer as Metlife. The proposition says that in low hiring cost locations, Continental is relatively more active than Metlife, despite the fact that Metlife is more efficient. This is driven by differences in span of control costs: Metlife, having more efficiency units, finds it relatively more costly to manage the marginal agent and therefore allocates the marginal agent to the large hiring cost locations where Continental is not able to serve. These two forces together generate spatial sorting in a distributional sense, as I depict in Figure 1.

The proposition does not specify which locations are low- or high-cost. However, I observe very specific spatial sorting patterns in the data that the model can replicate with more structure on f_s. The following corollary emphasizes sorting along a given spatial fundamental X_s, such as market size or income.

Corollary 2.1: Sorting Along Local Fundamentals

Suppose $\theta_j > \theta_{j'}$ and suppose Assumption 1 holds. Suppose further that f_s is only a function of X_s and is strictly increasing in X_s. Then $\mathbb{E}_j[X_s] > \mathbb{E}_{j'}[X_s]$, where

$$\mathbb{E}_j[X_s] = \sum_{s \in \mathcal{S}} \left(\frac{a_{js}}{\sum_{s'} a_{js'}} \right) X_s$$

is insurer j's agent-weighted average of local fundamental X_s.

Proof: See Appendix A.3.

The corollary is consistent with the empirical sorting patterns I report in Section 2.3. For example, if hiring costs are increasing in market size N_s, then the efficient insurers sort toward the large markets, while the inefficient insurers sort toward small markets. Similarly, if hiring costs are increasing in the share of high-type households η_s^h, then efficient insurers also sort toward high-elasticity markets, while inefficient insurers sort toward low-elasticity markets. This particular dimension of sorting implies an additional corollary relevant for pricing patterns across insurers.

Corollary 2.2: Price Dispersion

Suppose $\theta_j > \theta_{j'}$ and suppose Assumption 1 holds. If $f_s > f_{s'}$ implies $\eta_s^h > \eta_{s'}^h$ for all $s, s' \in \mathcal{S}$, then under uniform pricing, $p_j < p_{j'}$. Under flexible pricing, $p_{js} = p_{j's}$ for all j and all s.

Proof: See Appendix A.4.

Corollary 2.2 is consistent with the spatially biased pricing patterns documented in Section 2.3: if high-income households have higher elasticities than low-income households, then insurers sorting toward richer markets should also set lower prices.

3.4 The Effect of National Price Setting on the Spatial Distribution of Agents

National pricing affects insurer profitability through two margins. First, national pricing affects equilibrium markups in every location. Second, with heterogeneous insurers and an outside option, equilibrium price changes also affect sales volumes. The two effects compete with each other: if prices decline in a location relative to flexible pricing, markups fall unambiguously, while volume may rise or fall depending on the price responses of all other insurers.

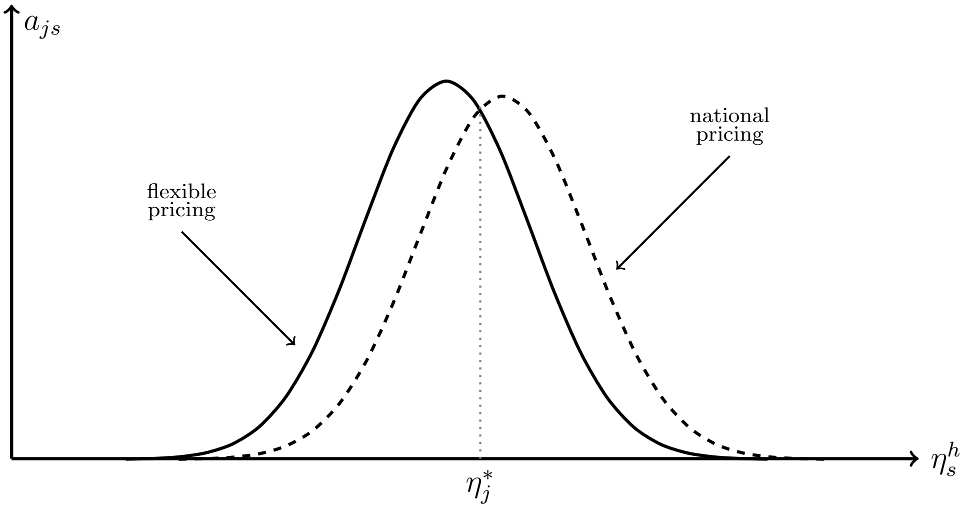
The magnitude of the volume effect is difficult to characterize with insurer-level heterogeneity. Nevertheless, I can prove the following result in a simple case with homogeneous firms and some structure on hiring costs:

Proposition 3: Geographic Responses to National Pricing

Suppose $\boldsymbol{\iota} \to \infty$, $\boldsymbol{\theta} \to \theta$, and f_s is solely a function of market size, $f_s = f(N_s)$. Then conditional on market size, there exists a cutoff η_j^{h*} such that $a_{js}^{\text{natl}} < a_{js}^{\text{flex}}$ if $\eta_s^h < \eta_j^{h*}$ and $a_{js}^{\text{natl}} > a_{js}^{\text{flex}}$ if $\eta_s^h > \eta_j^{h*}$.

Proof: See Appendix A.5.

Figure 2: The Effect of National Pricing on Insurer Location Decisions



Note: This figure displays agent distributions across regulatory regimes for a given insurer. The cutoff η_j^{h*} corresponds to the respective local high-income shares in which the insurers place an equal number of agents across regimes. Solid lines correspond to the flexible pricing regime and dashed lines correspond to the uniform pricing regime. The figure is conditional on market size N_s.

While the assumptions required for Proposition 3 are strong, the implications are important: national pricing induces a shift in in the geographic allocation of agents away from low-type locations and towards high-type locations. This reallocation is directly due to changes in equilibrium markups. Markups in low-type locations fall relative to flexible pricing since insurers average local elasticities across locations. Insurers are therefore less profitable and, as a result, they reduce the number of agents in low-type locations. They reallocate activity to high-type markets, where their markups and profitability increase. Figure 2 visualizes this reallocation.

This result has important implications for household welfare. Market penetration changes are positively correlated with price changes: lower prices (higher welfare) imply fewer agents and fewer households reached (lower welfare). The next section formalizes the way that welfare changes across these two margins and analyzes which households gain and which households lose.

3.5 The Welfare Consequences of National Pricing

Which households lose and which households gain from national pricing regulation? Taking the log difference in consumer welfare of type k households in market s across regulatory regimes, we have

$$\Delta \log \mathbb{W}_s^k \equiv \log \mathbb{W}_s^{k,\text{natl}} - \log \mathbb{W}_s^{k,\text{flex}} = \log P_s^{k,\text{flex}} - \log P_s^{k,\text{natl}}. \tag{13}$$

The next proposition decomposes the consumer welfare effects to first order into two components: a pricing margin component that comes from the change in prices, and an access margin component that comes from changes in agent placement and market penetration.

Proposition 4: Consumer Welfare Decomposition

To first order, the log change in consumer welfare in location s for type k households when moving from flexible to national pricing satisfies

$$\Delta \log(\mathbb{W}_s^k) \approx \frac{\iota_k}{\varepsilon_k - 1}\left[\underbrace{\int_{\mathcal{J}} \kappa_{js}^{\text{flex}} \left((p_{js}^{\text{natl}})^{1-\varepsilon_k} - (p_{js}^{\text{flex}})^{1-\varepsilon_k} \right) dj}_{\text{pricing margin effect}} + \underbrace{\int_{\mathcal{J}} \left(\kappa_{js}^{\text{natl}} - \kappa_{js}^{\text{flex}} \right) (p_{js}^{\text{natl}})^{1-\varepsilon_k} dj}_{\text{access margin effect}} \right]$$

Proof: See Appendix A.6.

The uniform pricing literature focuses on the pricing margin, e.g. Aparicio et al. (2021) and Daruich and Kozlowski (2023). Conditional on the location choices of each insurer, the pricing component measures the direct impact of national pricing regulation on welfare through price changes. The effects are positive for low-elasticity locations and negative for high-elasticity locations.

The new component relative to the uniform pricing literature is the access margin, which determines how much welfare changes conditional on national prices when insurers adjust their agents. From Proposition 3, market penetration changes in the opposite direction of prices, which dampens the pricing margin effects. Both effects will be negligible around the cutoff regions η_j^*, but may be large in the tails of the spatial high-type distribution. In these cases, the access margin effects may be large enough to fully offset or even reverse the pricing margin effects.

The relative strengths of the two effects depend crucially on a given household's demand elasticity. To give a stark example, let $\varepsilon_\ell \to 1$. In this case, type ℓ households no longer have any disutility from prices and care only about their idiosyncratic tastes. The pricing margin effects are therefore 0 for type ℓ households. When $\Delta \kappa_{js} < 0$ for the majority of insurers in location s, it follows that $\Delta \log \mathbb{W}_\ell^s < 0$: national pricing reduces low-type consumer welfare in low-type locations despite average prices being lower.

In general, the relative magnitude of the two effects are difficult to sign when not all insurers behave in the same way. For example, consider the location with the median share of high-type households. It may be that Metlife, who sorts toward high-type locations, lowers its price in the median location relative to flexible pricing, while Contintental, who sorts toward low-type places, increases their price in the same location. Additionally, if elasticity differences are large enough, the volume component of profitability may dominate the markup component, which could lead insurers to increase their market penetration in response to a decline in markups. The following proposition therefore characterizes which households lose and which ones gain in response to a set of changes for a particular insurer Δp_{js} and $\Delta \kappa_{js}$.

Proposition 5: Welfare Effects Across the Type Distribution

Suppose $p_{js}^{\text{natl}} < p_{js}^{\text{flex}}$ *and* $\kappa_{js}^{\text{natl}} < \kappa_{js}^{\text{flex}}$ *for insurer* j*. Consider a household with price elasticity* ε_i*. There exists a threshold* ε_{js}^* *such that the pricing margin dominates when* $\varepsilon_i > \varepsilon_{js}^*$ *and the access margin dominates when* $\varepsilon_i < \varepsilon_{js}^*$*.*

Proof: See Appendix A.7.

The overall welfare effect depends on the exact distribution of price and market penetration changes across insurers. The goal of the remainder of the paper is to estimate the model and the welfare effects of national pricing, which I turn to now.

4 Model Estimation

This section begins by laying out the quantitative extension to the model. I then discuss estimation strategy and present estimation results. Last, I test the model by predicting the number of agents in each location in different time periods and assessing the extent to which the model correlates with the data.

4.1 Quantitative Extension

I make three changes to the structure of the model. First, I allow household values to depend on insurer characteristics. Prices are only one component that households may care about when purchasing an insurance policy. Other factors, such as the size of the insurer, the financial rating of the insurer, or leverage may be important for household decisions. I therefore modify preferences to take the form

$$u_{ijs} = \log \iota_{k(i)} + \log \omega(\boldsymbol{X}_j^f) - (\varepsilon_{k(i)} - 1) \log p_j + \nu_{ijs}$$

where $\boldsymbol{X}_j^f$ is a vector of insurer characteristics. Second, I now allow for marginal cost heterogeneity to capture differences in prices that cannot be explained by heterogeneous markups. Third, I incorporate observed state-level premium revenue taxes t_s into the model. In Section 5, I manipulate the premium revenue taxes when I study place-based policies. I rebate taxes and profits back to households.

I also specify functional forms for hiring costs f_s and the span of control function $C(\bar{a}_j, \theta_j)$. Hiring cost are a function of market size and the share of high-income households, $f_s = \tau_0 N_s^{\tau_1} \eta_s^{\tau_2}$. I restrict $\tau_0 > 0$, but leave τ_1 and τ_2 unrestricted. Market size could be positively related to hiring costs through hiring volume: licensing a small number of agents may be simple, but hiring thousands may be increasingly costly, especially if expected agent turnover is increasing in hiring volume. On the other hand, market size may also be negatively correlated with hiring costs if it is generally more difficult to locate agents in small places. Income could reflect differences in education attainment for the average local agent. If less educated agents are more difficult to train, then we might expect $\tau_2 < 0$. But if more educated agents are difficult to attract due to having better outside options, it may also be that $\tau_2 > 0$.

Span of control costs take the functional form

$$C(\bar{a}_j, \theta_j) = \frac{\gamma_0}{\gamma_1} \left(\sum_{s \in \mathcal{S}} \theta_j a_{js} \right)^{\gamma_1} .$$

I assume $\gamma_0 > 0$ and $\gamma_1 > 1$ to satisfy the convexity assumption. A larger γ_1 implies stricter marginal span of control costs for large insurers, which generates stronger spatial sorting patterns.

4.2 Estimating Price Elasticities and Demand Components

I assume two household types: low-income and high-income. The choice of only 2 types is to economize on statistical power. Households are considered low-income if their income is below the national median, \$75,000, and are considered high-income if their income is above the median.[11]

To first order, insurer j's sales to income group k in location s are

$$\log S_{js} = \underbrace{\log a_{js} + \log \theta_j}_{\text{market penetration}} + \underbrace{\log \omega(\boldsymbol{X}_j^f)}_{\text{insurer characteristics}} - \underbrace{(\varepsilon_\ell - 1) \log p_j}_{\text{low-income elasticity}} + \underbrace{(\varepsilon_\ell - \varepsilon_h)\chi_s \log p_j}_{\text{relative elasticities}} + \text{FE}_s \tag{14}$$

where FE_s is a location-specific fixed effect. The fixed effect absorbs the market size component of market penetration, the type-specific price indexes, and the type-specific insurance values $\{\iota_k\}$. I assume a log-linear structure for the insurer characteristics:

$$\log \omega(\boldsymbol{X}_j) = \sum_{n=1}^{N} \omega_n X_{jn}. \tag{15}$$

I follow Koijen and Yogo (2016) and include log liabilities, leverage, financial ratings, return on equity, and an indicator for whether insurer j is a stock company. Appendix D.2 provides further details on variable construction and gives intuition for why they may enter in household preferences.

I use 10-year term life insurance premiums for 40 year olds averaged across male and female categories as the representative price. Since prices are endogenous, they are correlated with the error term. I therefore use two sets of supply shifters as instruments. First, I use the log of insurers' variable annuity reserve valuations. Insurers with high reserve valuations face larger shadow costs of capital as shown in Koijen and Yogo (2022). They may therefore reduce their life insurance prices to increase their immediate funds and push them farther from their risk-based capital con-

[11] I also present results where I further disaggregate types by income and race which I discuss later in this section.

straint. To the extent that households care only about the liquidity and solvency of an insurer, the exclusion restriction is that reserve valuation is uncorrelated with demand conditional on insurer characteristics.

My data for reserve valuations only span 2007-2015. As I discuss in Section 2, the NAIC-SBS data only includes agents licensed in 2022. I therefore only observe the number of insurer-agent pairs in a state in year t conditional on the agent being active at the time of data collection. While this measure is stable throughout the mid- to late-2010s, it becomes much more unreliable during the years before and after the financial crisis in 2008. I therefore do not include agent controls in the baseline specification. However, for robustness I approximate productivity θ_j as an insurer's total sales per agent, $\theta_j \approx \sum_s S_{js} / \sum_s a_{js}$. Since this measure is aggregated across states for each insurer, the long-run correlation is stronger than for the state-level agents.

I use a second Hausman et al. (1994) style instrument to address concerns that leaving out agents from the regression biases the price elasticity estimates. I use annuity prices for a given insurer from 2009 to instrument for life insurance prices from 2011-2018. Marginal costs share a common component across an insurer's product markets and should therefore be reflected in both life insurance and annuity prices. Since insurers do not regularly change their organizational structure, the cost component in both markets should also be correlated over time, justifying the relevance of the instrument. The exclusion restriction is that demand for annuities in 2009, the middle of the Great Recession, is uncorrelated with life insurance demand during the recovery.

Spatial variation in high-income expenditure shares is low at the state level relative to commuting zones, varying from 60% to 85%. To avoid power issues, I group states into high- and low-income bins using the median as the cutoff, and I refer to the indicator variable designating these two groups as $\tilde{\chi}_s = \mathbf{1}\{\chi_s \geq \text{median}(\boldsymbol{\chi})\}$. The estimates I report are the average elasticities of each of these groups of states. I use these estimates as approximations for the elasticities of low- and high-income households. This methodology underestimates the differences in demand elasticities across income groups. This implies that the counterfactuals in Section 5 are underestimating the true effects of national pricing since larger elasticity differences would imply a larger effect of national pricing on markups and, therefore, a larger effect on local agent choices.

Table 3 displays the results with p-values reported in parentheses. In all specifications, I estimate $\varepsilon_\ell, \varepsilon_h > 1$, implying that demand curves are downward sloping. The low-income elasticity ε_ℓ is only significantly different from 1 when using the variable annuity losses instrument, and is significant at the 10% level. However, the difference between elasticities is consistently different from zero and negative across specifications, implying $\varepsilon_h > \varepsilon_\ell$ as in Hastings et al. (2017). The difference is always significant at the 1% level under the annuity price instrument, and is significant at the 6% level when using variable annuity losses.

I also consider a specification using insurer-year fixed effects that further addresses measurement error in the number of agents and the productivity terms. This specification absorbs all observed

Table 3: Demand Estimation Results

	Variable Annuity Losses			*Annuity Prices*		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Price	−4.338	−4.533		−1.182	−0.304	
	(0.097)	(0.061)		(0.446)	(0.542)	
Log Price × $\tilde{\chi}_s$	−2.708	−2.038	−1.828	−2.882	−2.541	−2.701
	(0.052)	(0.056)	(0.032)	(0.000)	(0.000)	(0.000)
Size	1.016	0.834		0.375	0.427	
	(0.000)	(0.000)		(0.022)	(0.000)	
Leverage	−8.214	−5.426				
	(0.050)	(0.142)				
Rating	−2.402	−1.077		−1.703	−5.507	
	(0.145)	(0.441)		(0.582)	(0.000)	
Stock	−1.514	−0.771		0.583	0.737	
	(0.290)	(0.540)		(0.193)	(0.000)	
ROE	−1.105	−1.042		−0.308	−1.356	
	(0.045)	(0.068)		(0.852)	(0.031)	
Demand Controls	✓	✓	✓	✓	✓	✓
Productivity Proxy		✓			✓	
Agents				✓	✓	✓
Firm-Year FE			✓			✓
Obs	11326	10784	12190	949	949	949
Within R^2	0.155	0.172	-0.01	0.294	0.75	0.09
F	129.3	146.6	484.7	36.5	56.9	115.6

Note: Estimation results for regression equation (14). Columns (1)-(3) use the variable annuity losses instrument and do not include agents in the regression. Columns (4)-(6) use the annuity prices instrument and do include agents in the regression. Columns (1) and (4) do not incorporate productivity proxies. Columns (2) and (5) add the productivity proxies in. Columns (3) and (6) include insurer-year fixed effects. Standard errors are clustered at the insurer-year level. P-values are reported in parentheses.

and unobserved insurer characteristics and the productivity term. However, because prices are set at the insurer-year level, this specification also absorbs the price, so the low-income elasticity is not identified. The estimates are reported in columns (3) and (6) of Table 3. In all specifications, the difference in elasticities across income groups remain negative and statistically significant and have similar magnitudes to the baseline estimates.

In Appendix D.5, I further group states by share of non-white households to capture different elasticities across racial groups. The estimates continue to point to low-income households having lower elasticities. The results across racial groups differ by instrument, however. Using the variable annuity loss instrument, non-white low-income households have slightly higher elasticities than white low-income households. While this is at odds with the stylized fact in Section 2.3, it could reinforce the possibility that insurers do price discriminate on the basis of race. On the other hand, using the Hausman et al. (1994) instrument, I find that non-white households have lower elasticities than white households.

I use the results from column (4) in Table 3 for the remainder of the estimation for two reasons. First, the annuity price instrument allows me to control for the number of agents per insurer in each state, eliminating concerns that omitting agents biases the price elasticity results.[12] Second, the elasticity for the average household in the economy under (4) is approximately -3.48, which is the closest estimate to other demand elasticity estimates in the literature, e.g. Koijen and Yogo (2016) (-2.2) and Tang (2022) (-2.4). However, in Appendix E.1, I also estimate the model using the results in column (1) and draw similar conclusions when conducting counterfactuals.

4.3 Estimating Marginal Costs, Productivities, and Insurance Values

I recover productivity estimates and marginal cost estimates from the optimization conditions. To compute marginal costs, I input a guess for the model parameters $\psi = (\alpha, \{\gamma_k\}, \{\tau_k\})$ and $\{\iota_k\}$ and compute the implied hiring costs for each commuting zone and span of control costs for each insurer. I estimate sales shares for each insurer-commuting zone pair and aggregate across commuting zones to get each insurer's average elasticity. I then invert marginal costs from the optimal pricing condition given in Proposition 1.

To recover productivities $\{\theta_j\}$, I insert the marginal cost estimates and model parameters ψ into the agent optimality condition (12). Summing across the commuting zones in the NAIC-SBS sample, this condition can be written

$$S_j = \sum_{s \in \mathcal{S}} \left(\frac{f_s + C'(\bar{a}_j, \theta_j)}{(1 - t_s)p_j - \xi_j} \right) \left(\frac{\kappa(a_{js}, \theta_j, N_s)}{1 - \kappa(a_{js}, \theta_j, N_s)} \right) N_s^{\alpha}.$$

The right-hand side is strictly increasing in θ_j, so there exists a unique productivity level that rationalizes the observed agent and sales data given model parameters. When using parameter

[12] Hastings et al. (2017) show that biased agents may reduce demand elasticities. When I omit agents from the analysis, low-income elasticity estimates rise and high-income elasticities fall. This is consistent with Hastings et al. (2017) if low-income households are more sensitive to agent advice than high-income households.

guesses that imply S_j is less than the right hand side as $\theta_j \to 0$, I set $\theta_j = 0.001$. In practice, this restriction rarely binds.

Since the productivity estimates influence the sales shares of each insurer across commuting zones, I continue to update $\{\xi_j, \theta_j\}$ until convergence. I then group insurers into deciles based on their estimated demand components $\hat{\omega}_j$ and assign each representative insurer the average marginal cost and productivity in each decile. I report the resulting estimates in Appendix D.4.

I then solve for equilibrium price indices. I recover the type-specific life insurance values $\{\iota_k\}$ by aggregating the outside option share for each household type across commuting zones:

$$(1 - \text{Participation Rate})_k = \sum_{s \in \mathcal{S}} \left(\frac{E_s^k}{\sum_{s'} E_{s'}^k} \right) \left(1 + \iota_k \int \omega_j \kappa_{js} p_j^{1-\varepsilon_k} dj \right)^{-1}. \tag{16}$$

On the left hand-side, I use survey data on life insurance participation rates for each income type from Annuity.org (2023). The right hand side varies between 0 and 1 and is strictly decreasing in ι_k. There is therefore a unique solution for each income group that perfectly rationalizes observed participation rates in the data. Given the solution to (16), I restart the marginal cost-productivity loop and repeat until $\{\iota_k\}$ converges.

4.4 Estimating the Remaining Model Parameters

I now detail the simulated method of moments (SMM) procedure I use to solve for the model parameters ψ. I choose moments to match the function of each parameter. I calibrate the span of control parameters γ_0 and γ_1 to match the OLS slope parameters from the following sorting regressions:

$$\sum_{j \in \mathcal{J}} \left(\frac{a_{js}}{\sum_{j'} a_{j's}} \right) \log \omega_j = \beta_0^{\text{AS}} + \beta_1^{\text{AS}} \log \eta_s + \text{error}_s$$

$$\sum_{s \in \mathcal{S}} \left(\frac{a_{js}}{\sum_{s'} a_{js'}} \right) \log \eta_s = \beta_0^{\text{RS}} + \beta_1^{\text{RS}} \log \omega_j + \text{error}_j$$

The first regression provides a measure of absolute sorting: as local income increases, so does the size of the average insurer. The second regression is a measure of relative sorting: as the size of an insurer increases, so does the average income of its agents' markets.

Next, I calibrate hiring cost parameters τ_1 and τ_2 to match the relative allocation of agents across the commuting zone population distribution. For each $q \in \{50, 45, \ldots, 5\}$, I compute the average number of agents in the top q% of locations by market size and the average number of agents in the bottom q% of locations by market size and take the ratio of the two. The ratio is

Table 4: Internal Calibration Summary and Results

Moment Group	Parameter	Value	Moment	Data	Model
Sorting	γ_0	0.024	Relative Sorting: β_1^{RS}	0.019	0.016
	γ_1	1.536	Absolute Sorting: β_1^{AS}	0.781	0.938
	τ_1	0.815	Agent Allocation: β_0	2.206	1.901
	τ_2	-0.785	Agent Allocation: β_1	0.096	0.042
Size	τ_0	0.112	Top 20% Sales Share	0.729	0.640
	α	0.618	Agent-Firm Pairs per CZ	3982	5794
Participation	ι_h	0.501	High-Income Participation	0.597	0.597
	ι_ℓ	0.096	Low-Income Participation	0.374	0.374

Note: The value column reports the parameters that minimize the sum of squared deviations between data and model moments. The last two columns report the data-generated moments and the model-generated moments respectively.

decreasing exponentially in q, so I match the OLS coefficients from the regression

$$\log \frac{\mathbb{E}[a_c|N_s \text{ in top } q\%]}{\mathbb{E}[a_s|N_s \text{ in top } q\%]} = \beta_0 + \beta_1(50 - q) + \text{error}_q.$$

I calibrate τ_0 to match the sales share of the top 20% of insurers. Since τ_0 is a common cost component for all insurers, increasing τ_0 punishes small insurers relatively more than large insurers, increasing the sales share of the large insurers. Finally, I calibrate the market penetration size effect parameter α to match the average number of agent-insurer pairs per location.

Table 4 summarizes the parameters and moments and reports the results. Due to the strong non-linearities in the model, I cannot match the moments exactly, though several moments come close. The most mismatched moment is the average number of agent-insurer pairs per location.

Appendix D.6 documents the fit of the model. First, I regress total agents per commuting zone in the model on total agents per commuting zone in the data. The R^2 is 0.64 in logs and 0.70 in levels, which implies the model captures between 64-70% of the variation in agent availability across commuting zones. I then regress the log difference between model and data on the log population in each commuting zone. The slope is negative, implying that I overestimate agents in small markets relative to large markets. From the welfare decomposition in Proposition 4, this implies that pricing margin welfare effects will be overestimated relative to access margin effects in small markets relative to large markets.

I test how well the model can match the allocation of agents across commuting zones in a different time period in Appendix D.7. I solve the model using 2010 spatial fundamentals and compare the difference in agents over time to the observed differences in agents in the data. Since the NAIC-SBS data is not a true panel, I supplement the NAIC-SBS data with information on local brokers and financial intermediaries from the Quarterly Census of Employment and Wages. Regardless of the choice of intermediaries, the model can match changes in agents across commuting zones. I regress the change in total commuting zone agents in the model on changes in total commuting zone agents in the data and recover an R^2 of 0.61.

5 The Welfare Effects of National Pricing Restrictions

I now use the estimated model to conduct a variety of exercises. First, I consider the flexible price equilibrium and decompose spatial disparities in welfare into a pricing component and an access component following the logic of Section 3.5. Next, I analyze how national price setting affects both components across commuting zones and across household income types within each commuting zone. I then consider how regulators can target the access margin explicitly through place-based tax policies.

Throughout this section, the welfare effects are reported relative to the share of expenditures on life insurance. For example, an increase in life insurance welfare of 2% would translate to a $\beta \times 2\%$ increase in total welfare, where β is the life insurance expenditure share.

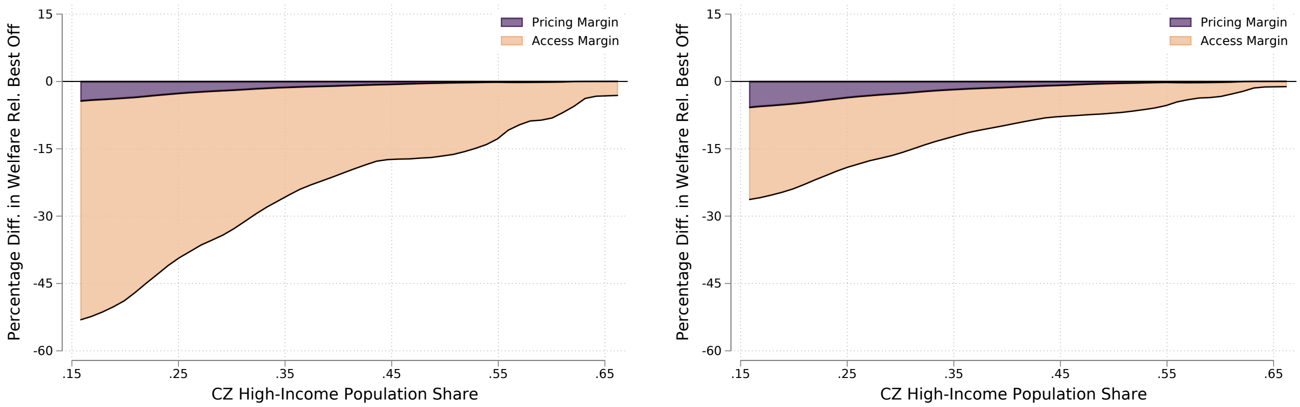
5.1 Decomposing Spatial Welfare Disparities

This section quantifies differences in household welfare across commuting zones in the flexible pricing equilibrium. Under flexible pricing, low-income commuting zones face higher prices, have fewer varieties, and have lower market penetration. Which margin is larger, and how does this depend on household income?

I first select the commuting zone with the highest average welfare (Santa Cruz). I then compare welfare in each commuting zone to welfare in Santa Cruz conditional on household type. I decompose the difference into a pricing component and an access component following the decomposition logic in Section 3.5.

Figure 3 plots welfare differences relative to Santa Cruz against commuting zone high-income population share. Price discrimination in the poorest commuting zone reduces low-income household welfare by 4.38% relative to low-income households Santa Cruz and reduces relative high-income household welfare by 5.81%. However, the bulk of the welfare differences come from the access margin. Due to differences in life insurance accessibility, low-income households in the poorest commuting zone are 48.88% worse off relative to low-income households in Santa Cruz, and high-income households in the poorest commuting zone are 20.63% worse off relative to high-income households in Santa Cruz. In percentage terms, disparities in life insurance access account for

Figure 3: Welfare Dispersion Under Flexible Pricing



(a) Low-Income Households

(b) High-Income Households

Note: This figure documents spatial dispersion in welfare relative to Santa Cruz, the location with the highest flexible pricing welfare, conditional on household income. The purple areas reflect disparities in prices and the tan areas reflect disparities in access. All lines are local polynomials estimated with the Epanechnikov kernel. Panel (a) considers low-income households and Panel (b) considers high-income households.

91.8% of welfare differences for low-income households and 78% of welfare differences for high-income households.

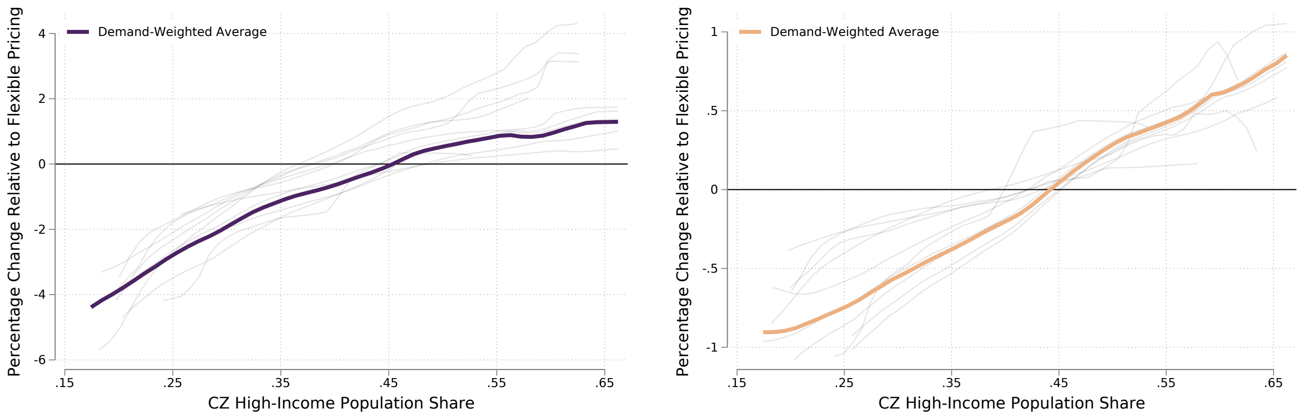
5.2 The Welfare Effects of National Price Setting

I start by analyzing how pricing and location decisions change after imposing national pricing restrictions. Figure 4a shows how prices change for each insurer across the spatial income distribution in response to the policy, and Figure 4b shows how market penetration changes. In each figure, the solid colored line is a demand-component-weighted average of the changes, and each gray line represents one of the ten insurer size deciles.

Both figures are consistent with the predictions of the theory. Prices fall in the poorest commuting zones by a little over 4% on average, while they rise by about 1.2% on average in the richest commuting zones. The policy therefore makes households in low-income places better off and high-income places worse off on the pricing margin, alleviating some of the spatial disparities reported in Figure 3. However, due to the effects on local profitability, market penetration declines by 1 percentage points on average in the poorest commuting zones and increases by about 0.8 percentage points on average in the richest commuting zones. This implies that the insurers' agent adjustments offset the welfare effects of price changes, reducing the effectiveness of the policy.

What does this mean for welfare at the local level? Figure 5a decomposes the welfare effects into pricing and access margins for each commuting zone, plotting the effects against high-income population share. For consistency with Figure 3, I also plot the log change in welfare relative to

Figure 4: The Effect of Uniform Pricing Regulation on Firm Decisions



(a) Log Prices

(b) Market Penetration

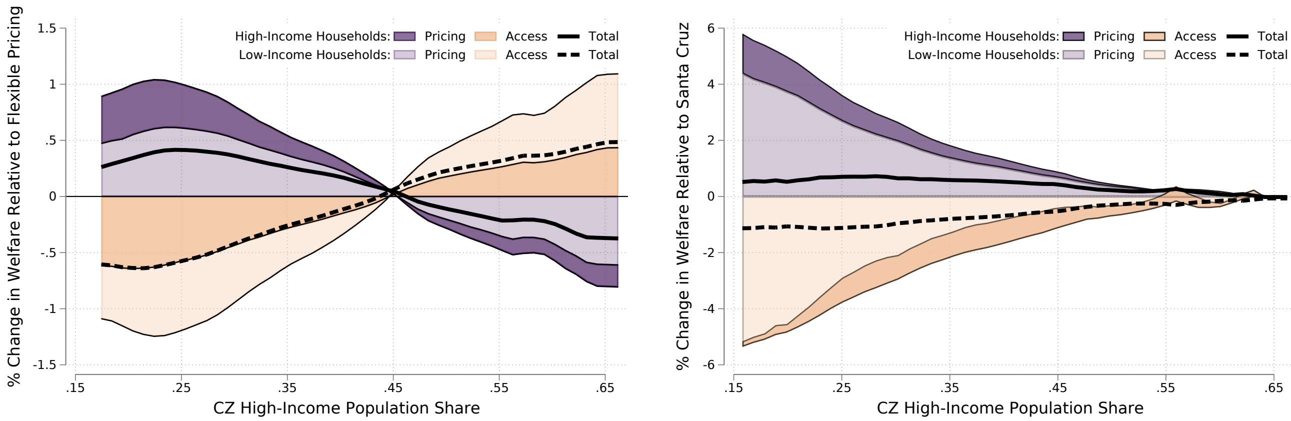
Note: This figure compares equilibrium insurer decisions under national pricing restrictions relative to flexible pricing. Each subfigure plots the decisions for each of the ten deciles of insurers as well as a demand-component-weighted average of the responses. All lines are local polynomials estimated with the Epanechnikov kernel. Panel (a) plots the log change in price across regimes against commuting zone high-income population share. Panel (b) plots the change in market penetration against commuting zone high-income population.

Santa Cruz in Figure 5b.

The pricing margin effects, displayed in Figure 5 as purple areas, are positive in poor commuting zones and negative in rich commuting zones. At best, high-income households gain by about 1% relative to the flexible pricing equilibrium, and low income households gain by about 0.6%. At worst, high-income households lose by about 0.8% and low-income households lose by about 0.4%. The policy is therefore redistributive on the pricing margin; it reallocates surplus from rich regions to poor regions. This is echoed in Figure 5b, which shows how all locations improve relative to Santa Cruz on the basis of prices. Moreover, the policy successfully equalizes prices across space, implying that the pricing disparities present in the flexible pricing equilibrium no longer exist.

The pricing effects are offset by the access margin effects. Low-income households in the poorest commuting zones are worse off by about 1.1%, and high-income households are worse off by about 0.6%. Combining the pricing and access margin effects, low-income households in poor commuting zones are worse off by about 0.5% relative to flexible pricing, while high-income households in these locations gain by about 0.4%. The reverse patterns hold in rich commuting zones: low-income households gain from increased access to insurance varieties, and high-income households lose due to facing higher prices.

Figure 5: The Spatial Welfare Effects of National Pricing Regulation



(a) Relative to Flexible Pricing

(b) Relative to Santa Cruz

Note: This figure documents percentage changes in welfare induced by national pricing against commuting zone high-income population share. All lines are local polynomials estimated with the Epanechnikov kernel. Dark areas represent high-income household changes and transparent areas represent low-income household changes. Purple areas represent the pricing margin and tan areas represent the access margin. Black lines reflect the sum of the pricing and access margins. Panel (a) reports changes relative to flexible pricing. Panel (b) reports the change in welfare relative to Santa Cruz.

5.3 A Complementary Place-Based Tax Policy

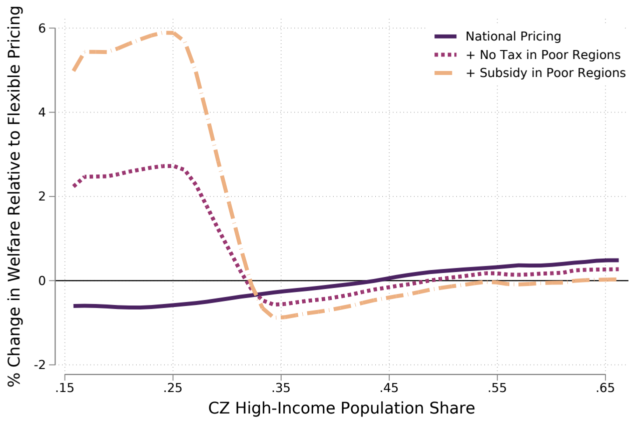
National pricing reduces pricing margin disparities but exacerbates access margin disparities. A potential policy solution is to use local tax policies to improve the profitability of insurers in low-profitability locations, potentially incentivizing insurers to place more agents in these locations.

I consider a policy that targets the bottom third of locations by local income, $\mathcal{S}_\ell$. I eliminate premium taxes in these locations and finance the loss in tax revenue by proportionately scaling up tax rates in the rich locations, $\mathcal{S}_h$. I solve for the tax scheme $\{t_s^*\}_s$ that makes the policy revenue neutral,

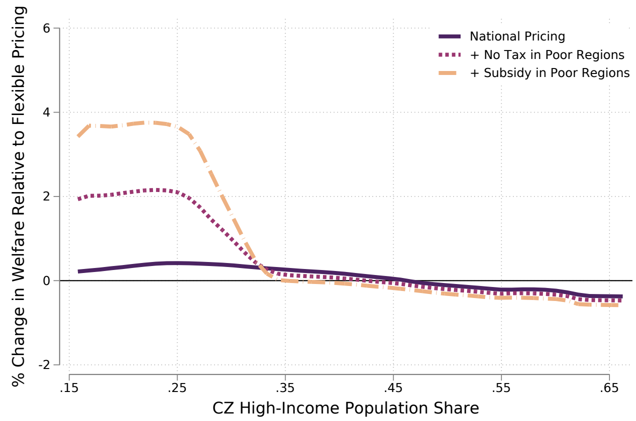
$$\int_{\mathcal{S}_h} \int_{\mathcal{J}} t_s^* S_{js}^* dj ds = \int_{\mathcal{S}} \int_{\mathcal{J}} t_s S_{js}^{\text{natl}} dj ds.$$

The policy can be scaled up by explicitly subsidizing insurers in poor places rather than simply eliminating taxes. There is a tradeoff to scale: if the scale is too large, the negative effects of the policy in high-income commuting zones may reverse the positive effects in the low-income commuting zones. To understand how well the policy scales, I also consider a policy in which I convert observed tax rates to subsidies in the poor locations. For example, if a location has an observed tax rate of 2%, I replace the tax with a subsidy of 2% for locations in $\mathcal{S}_\ell$, and again offset the tax revenue losses by increasing tax rates for locations in $\mathcal{S}_h$.

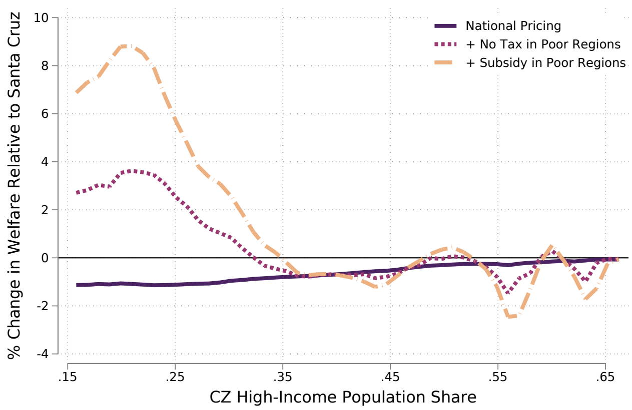
Figure 6: The Spatial Welfare Effects of Place-Based Policies



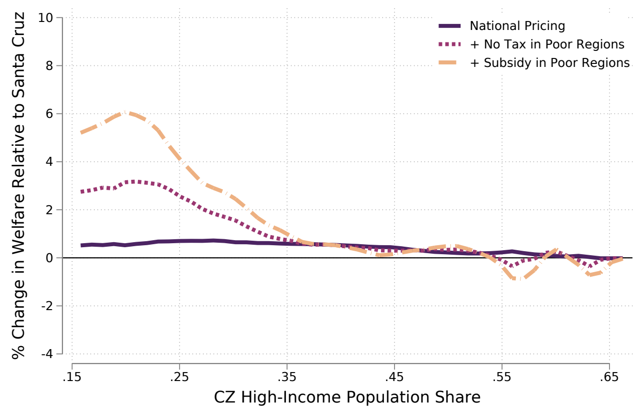
(a) Low-Income: Relative to Flexible Pricing



(b) High-Income: Relative to Flexible Pricing



(c) Low-Income: Relative to Santa Cruz



(d) High-Income: Relative to Santa Cruz

Note: This figure documents percentage changes in welfare induced by a combination of national pricing and place-based policies. All lines are local polynomials estimated with the Epanechnikov kernel. Purple lines reflect national pricing with observed state-level tax rates, magenta lines incorporate the no-low-income tax policy, and tan lines incorporate the subsidy policy. Panels (a) and (b) report the effects relative to flexible pricing and panels (c) and (d) report the effects relative to Santa Cruz. Panels (a) and (c) document the effects for low-income households and panels (b) and (d) document the effects for high-income households.

Figure 6 reports the welfare effects of the place-based policies relative to flexible pricing and relative to Santa Cruz. Both high- and low-income households gain in the treated commuting zones relative to flexible pricing as shown in Figures 6a and 6b. The effects are large: relative to flexible pricing, low-income households in subsidized commuting zones gain by 5.28% and high-income households gain by a little under 3.3% under the subsidy policy. In the high-income locations, low-income households lose by 0.44% and high-income households lose by 0.19%. These losses are small both relative to the gains in poor commuting zones and relative to the welfare effects under national pricing alone.

Figure 7: The Aggregate Welfare Effects of Place-Based Policies

(a) Utilitarian Welfare

(b) Welfare Dispersion

Note: This figure compares utilitarian and socialist welfare across policies. All bars are percentage changes relative to flexible pricing. Purple bars report the effects for national pricing with observed state-level tax rates, magenta bars incorporate the no-low-income tax policy, and tan lines incorporate the subsidy policy. Panel (a) shows changes in utilitarian welfare and Panel (b) shows changes in welfare dispersion, the negative of socialist welfare.

Figures 6c and 6d respectively report the effects of the place-based policies for low- and high-income households relative to Santa Cruz. The magnitudes are economically large in the subsidized commuting zones: low-income households in the poorest locations catch up by about 8 percentage points relative to Santa Cruz under the subsidy policy, and high-income households catch up by about 6 percentage points. Relative to flexible pricing, low-income welfare disparities in poor regions decline by 14% and high-income welfare disparities decline by about 20%.

I assess the aggregate effects of the policies in two ways. First, in Figure 7a, I compute changes in utilitarian welfare that puts equal weights on all households in the economy. Second, in Figure 7b, I analyze changes in spatial welfare inequality by computing the percent change in welfare variance across commuting zones.

National pricing without place-based policies leads to aggregate welfare losses for both planners. Utilitarian welfare declines by 0.03% under national pricing alone, and spatial welfare dispersion increases by about 1%. After incorporating the place-based policies, welfare increases for both measures relative to flexible pricing. The subsidy policy increases utilitarian welfare by 0.06% and decreases spatial welfare variance by about 18%. The decline in welfare variance is uniform across household types — about 16% for both high- and low-income households — but utilitarian welfare is not. Since the policies tax high-income commuting zones, high-income household utilitarian welfare declines 0.05% on average relative to flexible pricing. The overall gains are driven by low-income households, who gain by about 0.15% relative to flexible pricing.

6 Conclusion

This paper provides a framework to analyze how price regulation affects the spatial distribution of firm activity. When price regulation has a geographic component, firms naturally adjust away from the locations where the policy bites the most. In the life insurance industry — and the financial services industry in general — these responses may exacerbate financial access disparities and amplify, rather than dampen, inequality. I argue in this paper that regulators must take the access margin into account and target it explicitly to promote financial inclusion in the industry. Place-based policies are one potential set of tools that accomplish this.

That being said, the analysis in this paper ignores many aspects of discrimination that could be present beyond household preferences. The purpose of national pricing in the life insurance industry is to discourage racial discrimination. Even if minority households have similar tastes, insurers may view minorities as having meaningful differences in risk conditional on observable characteristics and may internalize this risk when setting prices. Incorporating this margin into the model would strengthen the effects of the policy and perhaps lead to different conclusions.

Further, absent an observed change in regulation, this paper cannot test directly whether the access channel is affected by the policy. However, there are two settings in which testing for the access channel may be plausible. First, annuity providers in the United Kingdom recently began pricing on postal codes, departing from observed national pricing documented in Finkelstein and Poterba (2004). This setting would be ideal to understand whether national pricing causes geographic segmentation.

Second, the Affordable Care Act (ACA) marketplace for health insurance enabled states to enforce uniform pricing within state-defined "ratings areas" that consisted of bundles of counties. Health insurers are not permitted to vary prices across counties within each of their ratings areas. (Fang and Ko (2020)) document that health insurers geographically segment by local risk within ratings areas, consistent with the mechanism in this paper. An extension to the Fang and Ko (2020) study that explores how health insurance participation varies within ratings areas due to this segmentation would inform the validity of the mechanism in the life insurance industry.

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A Proofs

A.1 Proof of Proposition 1

It will be convenient to prove this proposition for the general case of finitely many firms as in Atkeson and Burstein (2008), as this will be one of the main extensions of the model. To revert back to the monopolistic competition case, simply replace the market share components of the elasticities to 0.

Begin by calculating the optimal price in the pricing-to-market regime, $\mathcal{P} = \mathcal{P}^{\text{ptm}}$. Since firms are optimizing location by location, I'll do the calculation for an arbitrary location $s \in \mathcal{S}$. Recall that local profits for firm j take the form

$$\begin{aligned}\pi_{js} &= (p_{js} - \xi)\left(Q_{js}^h + Q_{js}^\ell\right) \\ &= (p_{js} - \xi)\left\{\theta_j \frac{\beta N_{js}^h w_h}{p_{js}}\left(\frac{p_{js}}{P_s^h}\right)^{1-\varepsilon_h} + \theta_j \frac{\beta N_{js}^\ell w_\ell}{p_{js}}\left(\frac{p_{js}}{P_s^\ell}\right)^{1-\varepsilon_\ell}\right\}.\end{aligned}$$

Differentiating firm j's profit function with respect to p_{js} gives

$$Q_{js}^h + Q_{js}^\ell - \left(\frac{p_{js}-\xi}{p_{js}}\right)\sum_{k=\ell,h}\left\{\theta_j\varepsilon_k \frac{\beta N_{js}^k w_k}{p_{js}}\left(\frac{p_{js}}{P_s^k}\right)^{1-\varepsilon_k} + \theta_j(1-\varepsilon_k)\frac{\beta N_{js}^\ell w_\ell}{p_{js}}\left(\frac{p_{js}}{P_s^\ell}\right)^{1-\varepsilon_\ell}\left(\frac{\theta_j\kappa_{js}^k p_{js}^{1-\varepsilon_k}}{(P_s^k)^{1-\varepsilon_k}}\right)\right\} = 0$$

Next, note that we can write the last part of the bracketed term as

$$\begin{aligned}\frac{\theta_j\kappa_{js}^k p_{js}^{1-\varepsilon_k}}{(P_s^k)^{1-\varepsilon_k}} &= \frac{\theta_j\kappa_{js}^k p_{js}^{1-\varepsilon_k}}{M_s R^{\varepsilon_k - 1} + \sum_{j'}\theta_{j'}\kappa_{j's}^k p_{j's}^{1-\varepsilon_k}} \\ &= \frac{p_{js}[\beta w_k N_s^k/(p_{js}(P_s^k)^{1-\varepsilon_k})]\theta_j\kappa_{js}^k p_{js}^{1-\varepsilon_k}}{M_s[\beta w_k N_s^k/(R^{-1}(P_s^k)^{1-\varepsilon_k})]R^{\varepsilon_k-1} + \sum_{j'}[\beta w_k N_s^k/(p_{j's}(P_s^k)^{1-\varepsilon_k})]\theta_{j'}\kappa_{j's}^k p_{j's}^{1-\varepsilon_k}} \\ &= \frac{p_{js}Q_{js}^k}{p_{\text{save}}Q_{\text{save},s}^k + \sum_{j'}p_{j's}Q_{j's}} \\ &= \sigma_{js}^k.\end{aligned}$$

where the first line uses the definition of P_s^k, the second line multiplies the numerator and denominator by $\beta w_s N_s^k (P_s^k)^{\varepsilon_k - 1}$ and then multiplies each term by p_{js}/p_{js}, and the third line recognizes that all of the terms can be taken together to write Q_{js}^k. The fourth line uses the definition of the within-market-income sales share across firms. It follows that we can rewrite the first order condition as

$$Q_{js}^h + Q_{js}^\ell - \left(\frac{p_{js}-\xi}{p_{js}}\right)\sum_{k=\ell,h}\theta_j\frac{\beta N_{js}^k w_k}{p_{js}}\left(\frac{p_{js}}{P_s^k}\right)^{1-\varepsilon_k}\left[\sigma_{js}^k + (1-\sigma_{js}^k)\varepsilon_k\right] = 0.$$

Recall the definition of the within-market-income elasticity, $\varepsilon_{js}^k = (1-\sigma_{js}^k)\varepsilon_k + \sigma_{js}^k$, and the high-income sales share, $\chi_{js} = Q^h_{js}/(Q^h_{js} + Q^\ell_{js})$. Dividing both sides by $Q^h_{js} + Q^\ell_{js}$, we can now write

$$1 - \left(\frac{p_{js} - \xi}{p_{js}}\right)\left[\chi_{js}\varepsilon^h_{js} + (1-\chi_{js})\varepsilon^\ell_{js}\right] = 1 - \left(\frac{p_{js} - \xi}{p_{js}}\right)\Delta_{js} = 0.$$

Solving for p_{js} implies

$$p_{js} = \left(\frac{\Delta_{js}}{\Delta_{js} - 1}\right)\xi,$$

which is the correct result given in the proposition. Turning to the uniform pricing case, note that the first order condition is just the sum of the derivatives of each local profit function,

$$\begin{aligned}
0 &= \sum_{s\in\mathcal{S}}\left\{Q^h_{js} + Q^\ell_{js} - \left(\frac{p_j - \xi}{p_j}\right)\sum_{k=\ell,h} Q^k_{js}\left[\sigma^k_{js} + (1-\sigma^k_{js})\varepsilon_k\right]\right\}\\
&= \sum_{s\in\mathcal{S}}(Q^h_{js} + Q^\ell_{js})\left\{1 - \left(\frac{p_j - \xi}{p_j}\right)\sum_{k=\ell,h}\frac{Q^k_{js}}{Q^h_{js} + Q^\ell_{js}}\left[\sigma^k_{js} + (1-\sigma^k_{js})\varepsilon_k\right]\right\}\\
&= \sum_{s\in\mathcal{S}}(Q^h_{js} + Q^\ell_{js})\left\{1 - \left(\frac{p_j - \xi}{p_j}\right)\Delta_{js}\right\}.
\end{aligned}$$

where the second line factors out $Q^h_{js} + Q^\ell_{js}$ and the third line substitutes in the definition for Δ_{js}. Multiplying and dividing through by p_j and dividing through by $\sum_s(Q^h_{js} + Q^\ell_{js})$, we can now write

$$\sum_{s\in\mathcal{S}}\underbrace{\left(\frac{p_j(Q^h_{js} + Q^\ell_{js})}{\sum_{s'} p_j(Q^h_{js'} + Q^\ell_{js'})}\right)}_{\equiv\delta_{js}}\left\{1 - \left(\frac{p_j - \xi}{p_j}\right)\Delta_{js}\right\} = 1 - \left(\frac{p_j - \xi}{p_j}\right)\sum_{s\in\mathcal{S}}\delta_{js}\Delta_{js} = 0.$$

Once again solving for p_j, we get the familiar formula

$$p_j = \left(\frac{\sum_s \delta_{js}\Delta_{js}}{\sum_s \delta_{js}\Delta_{js} - 1}\right)\xi = \left(\frac{\varsigma_j}{\varsigma_j - 1}\right)\xi.$$

This completes the proof. □

A.2 Proof of Proposition 2

Due to differences in relative profitability across firms within a market, I'll separate the proof into two cases: flexible pricing and uniform pricing.

Case 1: Flexible Pricing

Begin by comparing the optimality condition (12) across firm j and j'. Note that under flexible pricing, $p_{js} = p_{j's}$ for all s since they share the same marginal cost, so $\Phi_s(p_{js}) = \Phi_s(p_{j's})$. It follows that when $A_{js}, A_{j's} > 0$,

$$\frac{\kappa_A(A_{js}, N_s)}{\kappa_A(A_{js}, N_s)} = \frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}}. \tag{17}$$

Next, I need the following lemma.

Lemma A.2.1

Suppose $\mathcal{P} = \mathcal{P}^{flex}$ and $\theta_j > \theta_{j'}$. Then $\lambda_j > \lambda_{j'}$.

Proof: Suppose that instead, $\lambda_j < \lambda_{j'}$. Then from (17), since $\theta_j > \theta_{j'}$, we know that the right-hand side is always less than 1. By concavity of $\kappa(A, \cdot)$, it follows that $A_{js} > A_{j's}$ for all $s \in \mathcal{S}$. But this implies $\bar{A}_j > \bar{A}_{j'}$, so by convexity of $C(\cdot)$, it must be that $\lambda_j = C'(\bar{A}_j) > C'(\bar{A}_{j'}) = \lambda_{j'}$, which is a contradiction. □

To establish the proposition, note that by Lemma A.2.1, we have

$$\lim_{f_s \to 0} \frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}} = \frac{\lambda_j}{\lambda_{j'}} > 1, \qquad \lim_{f_s \to \infty} \frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}} = \frac{\theta_{j'}}{\theta_j} < 1.$$

Continuity implies there exists $f^*(j, j')$ such that the right hand side of (17) is equal to 1, while the monotonicity of the right hand side implies uniqueness. By concavity of $\kappa(A, \cdot)$, it follows that $A_{js} < A_{j's}$ when $f_s < f^*(j, j')$ and $A_{js} > A_{j's}$ when $f_s > f^*(j, j')$. □

Case 2: Uniform Pricing

For the uniform pricing case, I need to highlight a bit more structure since prices are different across firms and, as a consequence, local profitability is not equalized within a location. First, define

$$\Omega_s(p_j, p_{j'}) = \frac{\Phi_s(p_j)}{\Phi_s(p_{j'})} = \frac{(p_j - \xi) \sum_k \chi_s^k (P_s^k)^{\varepsilon_k - 1} p_j^{-\varepsilon_k}}{(p_{j'} - \xi) \sum_k \chi_s^k (P_s^k)^{\varepsilon_k - 1} p_{j'}^{-\varepsilon_k}}.$$

The following lemma characterizes a couple useful properties of Ω.

Lemma A.2.2

The relative profitability function $\Omega_s : \mathbb{R}_+^2 \to \mathbb{R}_+$ satisfies the following properties:

1. $\Omega_s(p_j, p_{j'})^{-1} = \Omega_s(p_{j'}, p_j)$
2. *If* $\text{sgn}(p_j - p_{j'}) = \text{sgn}(\varepsilon_\ell - \varepsilon_h)$, then $\Omega_s(p_j, p_{j'}) < 1$ when $\chi_s = 0$ and $\Omega_s(p_j, p_{j'}) > 1$ when $\chi_s = 1$
3. *If* $\text{sgn}(p_j - p_{j'}) = \text{sgn}(\varepsilon_\ell - \varepsilon_h)$, *then* $\Omega_s(p_j, p_{j'})$ *is increasing in* χ_s.

Proof: Point 1 is trivial. For Point 2 and 3, I prove the case for $\varepsilon_\ell < \varepsilon_h$. The proof of the opposite case is identical. Note that we can rewrite Ω_s as

$$\Omega_s(p_j, p_{j'}) = \frac{(P_s^\ell)^{\varepsilon_\ell - 1} p_j^{-\varepsilon_\ell} (p_j - \xi) + \chi_s[(P_s^h)^{\varepsilon_h - 1} p_j^{-\varepsilon_h} (p_j - \xi) + (P_s^\ell)^{\varepsilon_\ell - 1} p_j^{-\varepsilon_\ell} (p_j - \xi)]}{(P_s^\ell)^{\varepsilon_\ell - 1} p_{j'}^{-\varepsilon_\ell} (p_{j'} - \xi) + \chi_s[(P_s^h)^{\varepsilon_h - 1} p_{j'}^{-\varepsilon_h} (p_{j'} - \xi) + (P_s^\ell)^{\varepsilon_\ell - 1} p_{j'}^{-\varepsilon_\ell} (p_{j'} - \xi)]}.$$

When $\chi_s = 0$, $\Phi_s(\cdot)$ is optimized at $p_\ell = (1 - \varepsilon_\ell^{-1})^{-1}\xi$, and when $\chi_s = 1$, the optimal price is $p_h = (1-\varepsilon_h^{-1})^{-1}\xi$. Under uniform pricing, we therefore have $p_h < p_j < p_{j'} < p_\ell$. Hence, $\Omega_s(p_j, p_{j'}) < 1$ when $\chi_s = 0$ and $\Omega_s(p_j, p_{j'}) > 1$ when $\chi_s = 1$.

It remains to show that $\Omega_s(p_j, p_{j'})$ is monotonically increasing in χ_s. For brevity, define $H_k(p_j) = (P_s^k)^{\varepsilon_k - 1} p_j^{-\varepsilon_k}(p_j - \xi)$. Differentiating $\Omega_s(\cdot)$ with respect to χ_s, we have

$$\frac{\partial \Omega_s(p_j, p_{j'})}{\partial \chi_s} \propto [H_h(p_j) - H_\ell(p_j)][H_\ell(p_{j'}) + \chi_s\{H_h(p_{j'}) - H_\ell(p_{j'})\}] \\ - [H_h(p_{j'}) - H_\ell(p_{j'})][H_\ell(p_j) + \chi_s\{H_h(p_j) - H_\ell(p_j)\}]$$

Simplifying, this expression becomes

$$\begin{aligned}\frac{\partial \Omega_s(p_j, p_{j'})}{\partial \chi_s} &\propto [H_h(p_j) - H_\ell(p_j)]H_\ell(p_{j'}) - [H_h(p_{j'}) - H_\ell(p_{j'})]H_\ell(p_j) \\ &= H_\ell(p_{j'})H_\ell(p_j)\left[\frac{H_h(p_j)}{H_\ell(p_j)} - \frac{H_h(p_{j'})}{H_\ell(p_{j'})}\right] \\ &> 0\end{aligned}$$

since $H_\ell(p_j) < H_\ell(p_{j'})$ and $H_h(p_j) > H_h(p_{j'})$. □

From here, there are two further cases to prove. The relative optimality condition under uniform pricing is now

$$\frac{\kappa_A(A_{js}, N_s)}{\kappa_A(A_{js}, N_s)} = \Omega_s(p_{j'}, p_j)\left(\frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}}\right). \tag{18}$$

For the first case, suppose

$$\lim_{\chi_s \to 0} \Omega_s(p_{j'}, p_j)\frac{\lambda_j}{\lambda_{j'}} < 1.$$

If $\lambda_j < \lambda_{j'}$, then by the monotonicity property of Ω_s, we have that the right-hand side of (18) is always less than 1, implying $A_{js} > A_{j's}$ for all s. Plugging this into the marginal span of control costs leads to a contradiction as in the proof of Lemma A.2.1, and therefore

A.3 Proof of Corollary 2.1

Let X be a random variable. Note that for any two CDFs F and G, if F first-order stochastic dominates G, then $\mathbb{E}_F[X] > \mathbb{E}_G[X]$. It therefore suffices to prove that single crossing implies first order stochastic dominance (FSOD). I use $F \succ G$ to mean F first-order stochastic dominates G. For reference, note that $F \succ G$ by definition implies $F(x) \leq G(x)$, with the inequality strict on the interior of the support of X.

Order s by f_s (and, by assumption, X_s) and define s^* to be the largest s such that $f_s \leq f_{jj'}$. To begin, note that from Lemma A.2.1, we have that $A_j > A_{j'}$. It follows from Proposition 2 that for any $s \leq s^*$, we have

$$\mathcal{A}_{js} \equiv \frac{1}{\bar{A}_j}\sum_{s \leq s^*} A_{js} < \frac{1}{\bar{A}_{j'}}\sum_{s \leq s^*} A_{j's} \equiv \mathcal{A}_{j's}$$

By way of contradiction, suppose that there exists a $\hat{s} > s^*$ such that $\mathcal{A}_{j\hat{s}} > \mathcal{A}_{j'\hat{s}}$. If there also exists a $\tilde{s} > s^*$ such that $\mathcal{A}_{j\tilde{s}} \leq \mathcal{A}_{j'\tilde{s}}$, then

$$\mathcal{A}_{j\tilde{s}} =$$

A.4 Proof of Proposition ??

A.5 Proof of Proposition 3

First note that when $\boldsymbol{O} \to 0$ and $\boldsymbol{\theta} \to \theta$, $p_{js} = p_{j's}$ for all s and j and $\kappa_{js} = \kappa_{j's}$ for all j and s. Therefore,

$$\left(\frac{p_{js}}{P_s^k}\right)^{1-\varepsilon_k} = \frac{p_{js}^{1-\varepsilon_k}}{\int \kappa_{j's} p_{j's}^{1-\varepsilon_k} dj'} = \frac{1}{J\kappa_{js}}.$$

The relative profitabilities for a given firm in a particiular location s as a result satisfy

$$\frac{\Phi_{js}^{\text{natl}}(p_j)}{\Phi_{js}^{\text{flex}}(p_{js})} = \left(\frac{1-\xi/p_j^{\text{natl}}}{1-\xi/p_{js}^{\text{flex}}}\right)\left(\frac{\sum_k E_s^k (p_j^{\text{natl}}/P_s^{k,\text{natl}})^{1-\varepsilon_k}}{\sum_k E_s^k (p_{js}^{\text{flex}}/P_s^{k,\text{flex}})^{1-\varepsilon_k}}\right) = \frac{\Delta_{js}}{\zeta_j}\frac{\kappa_{js}^{\text{flex}}}{\kappa_{js}^{\text{natl}}}, \tag{19}$$

where $\Delta_{js} \equiv \delta_{js}^{\text{wh,flex}}\varepsilon_h + (1-\delta_{js}^{\text{wh,flex}})\varepsilon_\ell$ is the local demand elasticity in location s which is strictly increasing in η_s^h. Since firms are identical by assumption, the remainder of the proof drops the j subscript from all firm-specific variables. Conditional on being active in a location s under both regimes, we can take logs of the agent optimality condition 12 and write

$$\Delta a_s = \frac{N_s^\alpha}{\theta_j}\Big(\Delta \log \Phi_s - \Delta \log(f_s + \lambda_j)\Big). \tag{20}$$

where I define $\Delta x \equiv x^{\text{natl}} - x^{\text{flex}}$ for a given variable x. Therefore, the change in agents comes from direct changes in profitability and indirect changes in span of control costs. These are the two margins I focus on in the proof.

The proof proceeds as follows. First, I show that there exist locations in which agents fall and agents rise relative to flexible pricing. Next, I show that span of control costs are lower under national pricing relative to flexible pricing. Finally, I establish a monotonicity result relating the change in agents to differences in local income. The combination of these three results establishes the proposition.

Claim 1: *There exists locations in which agents decline under national pricing.*

Suppose on the contrary that $\kappa_{js}^{\text{natl}} \geq \kappa_{js}^{\text{flex}}$ for all s. Then from (19), we have that

$$\Delta \log \Phi_s = \log\left(\frac{\Delta_s}{\zeta}\right) + \log\left(\frac{\kappa_s^{\text{flex}}}{\kappa_s^{\text{natl}}}\right) < \log\left(\frac{\Delta_s}{\zeta}\right)$$

For $\eta_s^h \to 0$ or $\eta_s^h \to 1$, note that we have $\delta_s^{\text{w}h} \to 0$ or $\delta_s^{\text{w}h} \to 1$ respectively. Since $\zeta \in (\varepsilon_\ell, \varepsilon_h)$, there must exist an η_{s*}^h such that $\Delta_s < \zeta$, implying that for such a location, $\Delta \log \Phi_s < 0$.

From the assumption that $\kappa_{js}^{\text{natl}} \geq \kappa_{js}^{\text{flex}}$, it is also true that $a_{js}^{\text{natl}} \geq a_{js}^{\text{flex}}$ for all $s \in \mathcal{S}$, implying that $\lambda^{\text{natl}} > \lambda^{\text{flex}}$; thus, $\Delta \log(f_s + \lambda_j) > 0$. It follows that for $s*$, we have

$$\Delta a_{s*} = \frac{N_{s*}^{\alpha}}{\theta_j}\Big(\Delta \log \Phi_{s*} - \Delta \log(f_{s*} + \lambda_j)\Big) < 0 < \Delta a_{s*},$$

where the last inequality follows from the assumption. This is a contradiction, and thus, there must be at least one location such that $\Delta a_s < 0$. $\square$

Claim 2: *There exists locations in which agents increase under national pricing.*

This proof is nearly identical to the proof of Claim 1, so I omit many of the details. Suppose instead that $\kappa_s^{\text{natl}} \leq \kappa_s^{\text{flex}}$ for all locations. It follows that

$$\Delta \log \Phi_s > \log\left(\frac{\Delta_s}{\zeta}\right).$$

The assumption additionally implies that $\Delta\lambda < 0$, implying $\Delta \log(f_s + \lambda) < 0$. It follows that for η_s^h large enough, $\Delta_s > \zeta$, so

$$\Delta a_{s*} = \frac{N_{s*}^{\alpha}}{\theta_j}\Big(\Delta \log \Phi_{s*} - \Delta \log(f_{s*} + \lambda)\Big) > 0 > \Delta a_{s*},$$

which is again a contradiction. Therefore, there exists at least one location such that $\Delta a_s > 0$. $\square$

Claim 3: *Changes in agents are increasing in η_s^h conditional on market size.*

By way of contradiction, suppose instead that there exists two locations s and s' such that $\Delta_s > \Delta_{s'}$ (and therefore $\eta_s^h > \eta_{s'}^h$) but $\Delta a_s < \Delta a_{s'}$. From the definition of profitability (19), we have that

$$\frac{\Phi_s^{\text{natl}}}{\Phi_s^{\text{flex}}} = \frac{\Delta_s}{\zeta}\frac{\kappa_s^{\text{flex}}}{\kappa_s^{\text{natl}}} > \frac{\Delta_{s'}}{\zeta}\frac{\kappa_{s'}^{\text{flex}}}{\kappa_{s'}^{\text{natl}}} = \frac{\Phi_{s'}^{\text{natl}}}{\Phi_{s'}^{\text{flex}}}$$

The inequality follows from the fact that conditional on N_s, $\Delta\kappa_s < \Delta\kappa_{s'}$ if $\Delta a_s < \Delta a_{s'}$. Next, note that conditional on N_s, $\log(f_s + \lambda) = \log(f_{s'} + \lambda)$ since $f_s = f(N_s) = f(N_{s'}) = f_{s'}$. Putting these two results together gives

$$\Delta a_s - \Delta a_{s'} = \frac{N_s^{\alpha}}{\theta_j}\left[\underbrace{\Big(\Delta\Phi_s - \Delta\Phi_{s'}\Big)}_{>0} - \underbrace{\Big(\Delta \log(f_s + \lambda) - \Delta \log(f_{s'} + \lambda)\Big)}_{=0}\right] > 0.$$

This is a contradiction to the assumption that $\Delta a_s < \Delta a_{s'}$, and therefore, I conclude that $\Delta a_s > \Delta a_{s'}$ when $\eta_s^h > \eta_{s'}^h$. $\square$

It remains to put the claims together. From Claims 1 and 2, we know there exist locations such that $\Delta a_s < 0$ and $\Delta a_s > 0$. From Claim 4, Δa_s is strictly increasing in η_s^h. Therefore, by the intermediate value theorem, there exist a unique η_s^{h*} such that $\Delta a_s < 0$ if $\eta_s^h < \eta_s^{h*}$ and $\Delta a_s > 0$ if $\eta_s^h > \eta_s^{h*}$. $\square$

A.6 Proof of Proposition 4

Using the definition of the local price indices, note that we can write

$$\begin{aligned}
\log(P_s^k) &= \frac{1}{1-\varepsilon_k}\log\left(O + \int_{\mathcal{J}} \kappa_{js} p_{js}^{1-\varepsilon_k}\, dj\right) \\
&= \frac{1}{1-\varepsilon_k}\log\left[O\left(1 + O^{-1}\int_{\mathcal{J}} \kappa_{js} p_{js}^{1-\varepsilon_k}\, dj\right)\right] \\
&\approx \frac{1}{1-\varepsilon_k}\left[\log(O) + O^{-1}\int_{\mathcal{J}} \kappa_{js} p_{js}^{1-\varepsilon_k}\, dj\right] \\
&= -\frac{\log(O)}{\varepsilon_k - 1} - \frac{O^{-1}}{\varepsilon_k - 1}\int_{\mathcal{J}} \kappa_{js} p_{js}^{1-\varepsilon_k}\, dj
\end{aligned}$$

where the first two lines follow from the definition and the third line follows using the first-order approximation $\log(1+x) \approx x$. It follows by substituting this into the expression for $\Delta \mathrm{CS}_s^k$ that

$$\begin{aligned}
\Delta \mathrm{CS}_s^k &\approx \left[-\frac{\log(O)}{\varepsilon_k - 1} - \frac{O^{-1}}{\varepsilon_k - 1}\int_{\mathcal{J}} \kappa_{js}^{\mathrm{flex}} (p_{js}^{\mathrm{flex}})^{1-\varepsilon_k}\, dj\right] - \left[-\frac{\log(O)}{\varepsilon_k - 1} - \frac{O^{-1}}{\varepsilon_k - 1}\int_{\mathcal{J}} \kappa_{js}^{\mathrm{unif}} (p_{js}^{\mathrm{unif}})^{1-\varepsilon_k}\, dj\right] \\
&= \frac{O^{-1}}{\varepsilon_k - 1}\left[\int_{\mathcal{J}} \kappa_{js}^{\mathrm{unif}} (p_{js}^{\mathrm{unif}})^{1-\varepsilon_k}\, dj - \int_{\mathcal{J}} \kappa_{js}^{\mathrm{flex}} (p_{js}^{\mathrm{flex}})^{1-\varepsilon_k}\, dj\right] \\
&= \frac{O^{-1}}{\varepsilon_k - 1}\left[\int_{\mathcal{J}} \kappa_{js}^{\mathrm{unif}} (p_{js}^{\mathrm{unif}})^{1-\varepsilon_k}\, dj + \left(\int_{\mathcal{J}} \kappa_{js}^{\mathrm{unif}} (p_{js}^{\mathrm{flex}})^{1-\varepsilon_k}\, dj - \int_{\mathcal{J}} \kappa_{js}^{\mathrm{unif}} (p_{js}^{\mathrm{flex}})^{1-\varepsilon_k}\, dj\right) - \int_{\mathcal{J}} \kappa_{js}^{\mathrm{flex}} (p_{js}^{\mathrm{flex}})^{1-\varepsilon_k}\, dj\right] \\
&= \frac{O^{-1}}{\varepsilon_k - 1}\left[\int_{\mathcal{J}} \kappa_{js}^{\mathrm{unif}}\Big((p_{js}^{\mathrm{unif}})^{1-\varepsilon_k} - (p_{js}^{\mathrm{flex}})^{1-\varepsilon_k}\Big)\, dj + \int_{\mathcal{J}} \Big(\kappa_{js}^{\mathrm{unif}} - \kappa_{js}^{\mathrm{flex}}\Big)(p_{js}^{\mathrm{flex}})^{1-\varepsilon_k}\, dj\right].
\end{aligned}$$

Since $O^{-1}/(\varepsilon_k - 1) > 0$, it follows that $\Delta \log(\mathrm{CS}_s^k)$ is approximately proportional to the final bracketed term, as stated in the proposition. $\square$

A.7 Proof of Proposition 5

This proof follows from rewriting the expression for $\mathcal{I}_{js}^m + \mathcal{E}_{js}^m$, namely

$$\mathcal{I}_{js}^m + \mathcal{E}_{js}^m = \kappa_{js}^{\mathrm{unif}} (p_{js}^{\mathrm{ptm}})^{1-\varepsilon_m}\left[\left(\frac{p_{js}^{\mathrm{ptm}}}{p_{js}^{\mathrm{unif}}}\right)^{\varepsilon_m - 1} - \frac{\kappa_{js}^{\mathrm{ptm}}}{\kappa_{js}^{\mathrm{unif}}}\right].$$

First, under Assumptions in Proposition 4 [write out explicitly in the text], we know that $\mathrm{sgn}(p_{js}^{\mathrm{ptm}} - p_{js}^{\mathrm{unif}}) = -\mathrm{sgn}(\kappa_{js}^{\mathrm{ptm}} - \kappa_{js}^{\mathrm{unif}})$. Therefore, it will be sufficient to characterize the case when $p_{js}^{\mathrm{unif}} < p_{js}^{\mathrm{ptm}}$, since the analysis for the opposite case will be identical.

Under this case, it's clear that $(p_{js}^{\mathrm{ptm}}/p_{js}^{\mathrm{unif}})^{\varepsilon_m - 1}$ is increasing in ε_m. Since type m households are of measure 0 and don't affect firm decisions, we can take the resulting prices and $\kappa_{js}^{\cdot}$ as constant. Therefore, we know that the bracketed term is monotonically increasing in ε_m. Since this is the term that determines the sign of the total welfare effect, it suffices to simply show that the term has different signs when evaluated at the bounds $\varepsilon_m = 1$ and $\varepsilon_m \to \infty$.

The first is simple, since $\varepsilon_m = 1$ implies $(p_{js}^{\text{ptm}}/p_{js}^{\text{unif}})^{\varepsilon_m - 1} = 1$, and so the sign of the bracketed term is simply $\text{sgn}(\kappa_{js}^{\text{unif}} - \kappa_{js}^{\text{ptm}}) = -1$. On the other hand, note that with $p_{js}^{\text{ptm}} > p_{js}^{\text{unif}}$, we have that the bracketed term diverges toward positive infinity when $\varepsilon \to \infty$. By the intermediate value theorem, there must be ε_{jm}^* such that the bracketed term is 0. Monotonicity ensures that the remainder of the theorem holds. $\square$

B Model Extensions

B.1 Generalizing Household Type Heterogeneity

In the benchmark model there were two types of households, h and ℓ. This section generalizes the type space to a continuum $\varepsilon \sim G_s(\varepsilon)$ with support $(1, \infty)$. Wages are then denoted as a function of the type, $w(\varepsilon)$.

For each individual type, residual demand and price indices stay the same, but the aggregation at the local level changes. Now, total residual demand in location s facing firm j is

$$Q_{js} \equiv \int_1^\infty Q_{js}(\varepsilon) dG_s(\varepsilon) = \kappa_{js} \int_1^\infty \frac{E_s(\varepsilon)}{p_{js}} \left(\frac{p_{js}}{P_s(\varepsilon)} \right)^{1-\varepsilon} dG_s(\varepsilon). \tag{B.1.1}$$

where $E_s(\varepsilon) \equiv \beta N_s w(\varepsilon) \eta_s(\varepsilon)$ is the mass of type-ε household expenditure. The setup for each firm and the definition of equilibrium are unchanged relative to the baseline model.

The main change comes from the pricing proposition. It follows that now we can define

$$\Delta_{js} \equiv \int_1^\infty \varepsilon \chi_{js}(\varepsilon) dG_s(\varepsilon), \qquad \chi_{js}(\varepsilon) \equiv \frac{p_{js} Q_{js}(\varepsilon)}{\displaystyle\int_1^\infty p_{js} Q_{js}(\varepsilon') dG_s(\varepsilon')}.$$

The remainder of the optimal pricing results remain true. Up to this point, the generalization has seemed to only complicate the model. However, recall that in the benchmark model, it was a bit complicated to sign the welfare effects in the case that prices and market penetration moved in the same direction. Here, since each type is infinitesimal, Proposition 5 is an exact result and pinpoints precisely which households gain and which households lose conditional on equilibrium outcomes.

B.2 Microfounding Market Penetration

This section derives a microfoundation for the market penetration function following Arkolakis (2010). Let $\kappa(A)$ denote the share of households reached with $A \equiv \theta a$ efficiency units. The microfoundation rests on the following assumptions:

Assumption 2: Market Penetration

1. *Each agent hired in a location reaches $N^{1-\alpha}$ households, $\alpha \in [0, 1]$.*

2. *The probability that a new efficiency unit reaches a household for the first time is given by* $(1-\kappa(A))^\beta$, $\beta \geq 0$.

The assumption uses the notation $A = \theta\theta a$ for efficiency units. Under Assumption 2, the marginal change in the number of households reached through new agents is

$$\kappa'(A)N = N^{1-\alpha}[1-\kappa(A)]^\beta. \tag{B.2.1}$$

Integrating both sides with the initial condition $\kappa(0) = 0$, we get

$$\int_0^A \frac{\kappa'(x)}{[1-\kappa(x)]^\beta} dx = N^{-\alpha}A.$$

Define $u = \kappa(x)$, so $du = \kappa'(x)dx$. Then we can rewrite the problem as

$$\begin{aligned} N^{-\alpha}A &= \int_0^{\kappa(A)} [1-u]^{-\beta} du \\ &= \frac{[1-\kappa(A)]^{1-\beta} - 1}{1-\beta}. \end{aligned}$$

Solving for $\kappa(A)$, we have

$$\kappa(A) = 1 - \left[1 - (1-\beta)\frac{A}{N^\alpha}\right]^{\frac{1}{1-\beta}}.$$

For the quantitative model, I use the limiting case $\beta \to 1$. Going back to the differential equation (B.2.1), we can substitute $\beta = 1$ to get

$$\int_0^A \frac{\kappa'(x)}{1-\kappa(x)} dx = -\log(1-\kappa(A)) = N^{-\alpha}A.$$

Solving for $\kappa(A)$, we come to the function used in the main text:

$$\kappa(A) = 1 - \exp\Big(-AN^{-\alpha}\Big).$$

B.3 Interpreting Demand As Relative to Actuarial Value

B.4 Microfounding Heterogeneous Price Elasticities with Bequest Motives

This section shows how price elasticity heterogeneity can emerge when households have heterogeneous preferences over leaving bequests. The derivation is very stylized, but admits a simple log-linear structure that maps exactly to the specification in (7).

Consider a household that matches with an insurer that sets a price p. At time $t = 0$, the household commits to paying premiums p in every period for q units of life insurance to leave to its heirs. With probability π each period, the household passes away and leaves its bequests. With probability $1-\pi$, the household survives and consumes their net-of-insurance earnings, $w - pq$. Their preferences are then

$$U(\beta, \psi, w) = \max_{q \geq 0} \ \log(w - pq) + \sum_{t>0} \beta^t \Big[(1-\pi)\log(w-pq) + \pi\psi\log(q)\Big], \tag{B.4.1}$$

where $\beta < 1$ is the discount factor for this household and $\psi \geq 0$ is their preferences for leaving bequests. The pair (β, ψ) is heterogeneous across households. I assume that there is no wage growth and that death is i.i.d. over time. With commitment, the problem reduces to

$$U(\beta, \psi, w) = \max_{q \geq 0} \left(\frac{1-\beta\pi}{1-\beta}\right)\log(w-pq) + \frac{\beta\pi\psi}{1-\beta}\log(q).$$

With the log-log structure, optimal insurance expenditures are a constant fraction of the wage, with the expenditure share given by

$$\frac{pq}{w} = \frac{\beta\pi\psi}{1+\beta\pi(\psi-1)}. \tag{B.4.2}$$

Substituting the expenditures back into the utility function (B.4.1), we have

$$U(\beta, \psi, w) = \iota(\beta, \psi, w) - \Big(\varepsilon(\beta, \psi) - 1\Big)\log(p), \tag{B.4.3}$$

where $\varepsilon(\beta, \psi) = 1 + \beta\pi\psi/(1-\beta)$ and the constant term $\iota(\beta, \psi, w)$ satisfies

$$\iota(\beta, \psi) = \left(\frac{1-\beta\pi}{1-\beta}\right)\log\left(\frac{1-\beta\pi}{1+\beta\pi(\psi-1)}\right) + \left(\frac{\beta\pi\psi}{1-\beta}\right)\log\left(\frac{\beta\pi\psi}{1+\beta\pi(\psi-1)}\right) + \left(\frac{1+\beta\pi(\psi-1)}{1-\beta}\right)\log(w).$$

The household's value for insurer j is then their indirect utility $U(\beta, \psi)$ plus an idiosyncratic preference shock ν:

$$u_{ij} \equiv u_j(\beta_i, \psi_i, w_i) = \iota(\beta_i, \psi_i, w_i) - \Big(\varepsilon(\beta_i, \psi_i) - 1\Big)\log(p_j) + \nu_j, \tag{B.4.4}$$

which is precisely the functional form given in the main text, (7). Given estimates of $\iota(\beta, \psi, w)$ and $\varepsilon(\beta, \psi)$ and values for w and π, I can invert the expressions to back out (β, ψ).

B.5 Optimal Pricing with Heterogeneous Costs

The benchmark model assumes that marginal costs are equalized across firms, interpreting them solely as expected payouts to deceased claimants. However, as I note in the text, these costs could be heterogeneous for a number of reasons. At the firm level, marginal costs could incorporate the shadow cost of capital due to restrictive statutory capital constraints as in Koijen and Yogo (2015) or differences in underwriting costs. At the geographic level, perhaps there are differences in realized mortality rates that firms would like to take into account, or perhaps there are labor costs that translate into marginal costs that vary spatially.

In the case with differences in marginal costs across firms and across space, we can write the first order condition of firm j with respect to their uniform price, getting

$$0 = \sum_{s \in \mathcal{S}} (Q^h_{js} + Q^\ell_{js}) \left[1 - \left(\frac{p_j - \xi_{js}}{p_j} \right) \Delta_{js} \right] = \sum_{s \in \mathcal{S}} \delta_{js} \Big[p_j - (p_j - \xi_{js}) \Delta_{js} \Big]. \tag{B.5.5}$$

Solving for p_j, we now come to

$$p_j = \frac{\sum_{s \in \mathcal{S}} \delta_{js} \Delta_{js} \xi_{js}}{\sum_{s \in \mathcal{S}} \delta_{js} \Delta_{js} - 1}. \tag{B.5.6}$$

When there is no spatial heterogeneity in costs, this simply reduces to $p_j = (1 - 1/\varsigma_j)\xi_j$ as in the benchmark case, and we can infer heterogeneous marginal costs using estimates of the elasticities and using sales shares across regions for firms. When there is no firm-specific heterogeneity, equation (B.5.6) provides a system of equations through which I can back out marginal costs. In particular, define

$$X_{js} = \frac{\delta_{js} \Delta_{js}}{\sum_{s \in \mathcal{S}} \delta_{js} \Delta_{js} - 1}.$$

Then we can write $p_j = \boldsymbol{\xi}' \mathbf{X}_j + u_j$, where u_j is statistical error. Therefore, regressing p_j on $\{X_{js}\}_s$ allows me to recover the vector of location-specific marginal costs, $\boldsymbol{\xi}$, where I use estimates $\{\hat{\varepsilon}_k\}_{k=\ell,h}$ found in Section 4 and observed sales shares across states to build $\{X_{js}\}$.

B.6 Endogenizing Local Fees

Assume there is a mass of life insurance agencies in the economy, $n \in [0, 1]$, that search for agents in each market. Each agency earns fees f_s when insurers license an agent, but must pay training costs of c_i for each agent i hired where c_i is a random variable that could depend on household characteristics such as income or education. If an agency hires L_s agents in location s, their operating profits are $(f_s - \mathbb{E}_s[c_i])L_s$. Here, $\mathbb{E}_s[c_i]$ is the expected training cost of agents in i given the distribution of household characteristics in location s.

Agencies also incur isoelastic search costs that they pay in units of the numeraire consumption good. With these ingredients, a given agency n faces the optimization problem

$$\pi^n_s = \max_L \left\{ (f_s - \mathbb{E}_s[c_i])L_s - \frac{\Gamma_s}{\varsigma + 1} L^{\varsigma+1} \right\}.$$

I allow Γ_s to vary by location to potentially capture differences in search frictions across locations. The solution to this problem satisfies

$$f_s = \mathbb{E}_s[c_i] + \Gamma_s \Big(L^n_s \Big)^\varsigma.$$

In a symmetric equilibrium, $L^n_s = L_s$ for all n. Further, under market clearing, agent supply must equal agent demand. Putting these two notions together gives the equilibrium hiring costs,

$$f_s = \mathbb{E}_s[c_i] + \Gamma_s a^\varsigma_s, \qquad a_s \equiv \int_{\mathcal{J}} a_{js} dj.$$

B.7 Variable Markups and Oligopolistic Competition

The baseline model assumes that the number of firms is large enough to effectively render the market structure to be monopolistic competition. I could instead assume that the set of firms is small and allow firms to internalize the effect of their choices on equilibrium price indices $\{P_s^k\}_{s,k}$.

As I show in the proof of Proposition 1 in Appendix A.1, the key difference is that the firm-location-specific elasticity Δ_{js} now satisfies

$$\Delta_{js} = \chi_{js}\varepsilon_{js}^h + (1-\chi_{js})\varepsilon_{js}^\ell, \qquad \varepsilon_{js}^k \equiv \varepsilon_k - \underbrace{(\varepsilon_k - 1)\sigma_{js}^k}_{\text{market power}}$$

where, as before, σ_{js}^k is firm j's market share of location s, type k households. With finitely many firms, the ones with high market shares face lower demand elasticities, which leads to higher markups.

The other difference is in the agent placement decisions. Local profitability now must be written

$$\Phi_s\Big(p_{js}, \{\sigma_{js}^k\}_k\Big) = E_s\Big[\chi_s(1-\sigma_{js}^k)\phi_{js}^h(p_{js}) + (1-\chi_s)(1-\sigma_{js}^\ell)\phi_{js}^\ell(p_{js})\Big]$$

where the type-specific profitability terms $\{\phi_{js}^k(p_{js})\}_k$ are unchanged. Why do the market shares show up in the agent placement decisions? Since the price indices are a function of the distribution of market penetration $\{\kappa_{js}\}_j$, firms know that by increasing their presence in a market, they lower the price index, making them relatively less profitable. Therefore, when their market share is high, they have a weaker incentive to expand more in a location.

C Additional Tables and Figures

This section presents several tables alluded to but not included in the main text.

D Additional Details on Data and Model Estimation

D.1 Ruling Out Within-Group Price Discrimination

If insurers use their group structure to price discriminate, we should see significant differences in their pricing strategies across insurers within the group. To test for this, I estimate the following regression:

$$\log p_j^{am} = \gamma_g^{am} + \gamma_j^{am} + \varepsilon_{jg}$$

for each age-maturity pair in the data. For each pair, I run a variance decomposition to assess whether group or insurer fixed effects explain the majority of the data.

Table C.1: Agents in Available US States

State	Number of Insurers	Number of Agents	Agent Density	Agent-CZ Concentration	Number of CZs
Alabama	271	13783	7.30	0.10	19
Arkansas	271	9128	7.80	0.13	21
Connecticut	235	10997	7.94	—	1
Delaware	243	971	2.62	0.26	2
Iowa	270	12161	9.55	0.09	26
Massachussetts	212	13021	4.92	0.73	6
Montana	253	2738	6.28	0.10	25
No. Carolina	297	33503	8.31	0.12	24
No. Dakota	220	2992	9.32	0.14	22
Nebraska	285	7365	9.61	0.28	27
New Hampshire	213	3239	6.01	0.76	4
New Jersey	247	26523	8.11	0.30	3
New Mexico	225	2362	2.98	0.32	16
Oklahoma	291	13652	9.14	0.24	22
So. Carolina	288	18799	9.58	0.08	11
Tennessee	352	27989	10.60	0.13	25
Vermont	180	959	3.65	0.30	5
Wisconsin	284	17648	7.42	0.11	19
West Virginia	255	3910	5.32	0.07	20
All States	443	221740	7.82	0.02	282

Note:

D.2 Demand Component Details

D.3 Lapsation Sensitivity Analysis

This section reports alternative estimates for the demand estimation with alternative lapsation rate assumptions.

Table C.2: Life Insurance Prices by Category

Category	Insurers	Mean	SD	Min	Max
Age					
... 30 y.o.	70	1.35	0.38	0.82	3.02
... 40 y.o.	70	0.90	0.24	0.55	1.73
... 50 y.o.	70	0.75	0.19	0.47	1.47
Sex					
... Female	70	1.07	0.43	0.47	3.02
..... Male	70	0.94	0.32	0.54	2.14
Maturity					
... 10-year	68	1.15	0.45	0.54	3.02
... 20-year	67	0.90	0.31	0.47	2.16
... 30-year	55	0.94	0.29	0.54	1.98
All Categories	70	1.00	0.38	0.47	3.02

Note:

Table C.3: Fact 3 Results

test	test	test

D.4 Firm Parameter Estimates

This section graphically reports the distribution of demand components, marginal costs, and productivities of insurers for which I have price data.

D.5 Incorporating Racial Demographics in Demand Estimation

D.6 Model Fit

D.7 Overidentification Test: Predicting Agents In Other Time Periods

E Additional Details on Data and Model Estimation

E.1 Estimating the Model Using VA Loss Instrument Elasticities