Equal Prices, Unequal Access

The Effects of National Pricing in the US Life Insurance Industry

Derek Wenning[†]

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Abstract

Regulators often promote financial inclusion by restricting prices. In response, firms may reduce the supply of their product, implying that some households lose from reduced access. This paper explores this tradeoff in the context of national price setting regulation 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 differentiated life insurance products. 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. Under flexible pricing, welfare differences between the poorest commuting zones and the richest commuting zone are between 0.4-0.95% of yearly income, most of which comes from differential access to insurers. National pricing amplifies spatial access disparities due to the geographic reallocation of insurers toward richer markets. Place-based tax policies that target the access margin reduce welfare differences between poor and rich commuting zones by 10.3-20.6%.

1   Introduction

Regulators often try to promote financial inclusion through 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. For example, this is the motivation behind credit card interest rate caps (Guenette (2020)), fixed-rate disaster lending (Begley et al. (2023)), and ratings areas in the ACA health insurance marketplace (Fang and Ko (2020)), to name a few. However, these policies may have adverse effects if firms optimally respond by reducing the availability of their products for certain households. 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, a relationship consistent with my results that I will discuss later. Consider the case of Metlife, a large life insurer in the United States. Absent regulation, Metlife would optimally set a high markup in poor markets like Detroit and a low markup in rich markets like New York City. Under national pricing, Metlife's markups fall in Detroit and rise in New York City. The policy is successful on this margin: life insurance is now more affordable for poor households in Detroit. However, since their Detroit markup is no longer optimal, Metlife may respond to the policy by reducing their operations in Detroit, perhaps by laying off their insurance agents or closing a branch, and reallocate their efforts to the relatively profitable New York. Therefore, although Metlife's prices in Detroit are lower, households in Detroit will be less able to access Metlife's 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 local life insurance availability. 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 has a lower financial rating 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 the agents depend on local hiring costs, an insurer's marketing productivity, and an insurer's overall size through span of control costs. With enough structure on hiring costs, these ingredients generate spatial sorting in a distributional sense: relative to unproductive insurers like Continental, Metlife is more active in large and rich locations like New York, but due to heightened span of control costs is less active in poor locations like Detroit.

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 local operating profitability, which directly impact 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 Metlife's 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 as 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 inequality in welfare under flexible price setting. I evaluate welfare differences across commuting zones using compensating differentials. For example, how much does a given household in Detroit need to be compensated to equate their welfare with an identical household in the best-off commuting zone? I find that low-income households in the poorest decile of commuting zones on average need to be compensated $351 per year, or 0.95% of their yearly income, and high-income households need to be compensated $506 per year, or 0.4% of their yearly income. These magnitudes are comparable to the literature on underdiversification (e.g. Calvet et al. (2007)) and suboptimal long-term investment choices (e.g. Koijen et al. (2016)).

Differences in access to insurers, as opposed to differences in prices, drive the results: in the poorest decile of commuting zones, 94.3% of low-income household compensation and 81.8% of high-income household compensation is due to the access margin. This implies that part of what drives suboptimal investment choices is the inability of some households to access investment opportunities at the local level.

Next, I evaluate the welfare effects of the national pricing policy. By design, national pricing eliminates the pricing disparities across commuting zones. However, in response to the policy, insurers reallocate their agents toward high-income commuting zones, exacerbating the access disparities in poorer regions. The effects are strong enough to amplify spatial inequality for low-income households: in the poorest decile of commuting zones, the average compensating differential increases by $10 per year relative to the flexible pricing equilibrium. Since high-income households are less sensitive to the access margin, spatial inequality amongst high-income households declines: their compensating differential decreases by $16 per year in the poorest decile of commuting zones.

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 insurer 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 into poorer regions. In the treated commuting zones, low-income compensating differentials decline on average by $40-$70 (11.1-19.4%) and high-income compensating differentials decline on average by $50-$100 (10.3-20.6%) relative to national pricing alone, depending on the size of the policy. Losses are small for non-treated commuting zones, with compensating differentials increasing by at most $1 per year for both low- and high-income households.

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 disparities in access, 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 de-

veloping 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

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[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 48% of sales come from within the county an agent is located in.[4] 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,

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[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.

[4]The authors consider the market for annuities rather than life insurance. However, many advisors sell both, so I consider this to be a reasonable proxy.

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 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.[5] 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.[6] Survival probabilities

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[5]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.

[6]I choose a 5% lapsation rate based on the national average lapsation rate in 2018. This measure is consistent

are taken from the 2015 Valuation Basic Table provided by the American Society of Actuaries.[7] 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.[8] 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.[9]

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.

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if lapsation rates do not differ across firms. I run all subsequent analysis with an assumed lapsation rate of 0% and find similar results.

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

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

[9]I perform a sensitivity analysis with respect to the assumed lapsation rate in Appendix D.2. The results are nearly identical to the baseline lapsation assumption of 5%.

TABLE 1: AGENTS IN THE CROSS SECTION OF COMMUTING ZONES

| Average... | All CZs | CZ High-Income Share Quintile | | | | |
		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:

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

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

11

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.[10] In the quantification, I assume that types are associated 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.[11] 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

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

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[10]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.

[11]I show in Appendix B.8 how the framework can be extended to include digital platforms as a form of customer acquisition. Since I do not have data on online sales, I load everything on local agents for the benchmark model.

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

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

where $\{Q_s^k(\cdot)\}_k$ are the demand curves for type k households. The 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 $\mathcal{P}$:

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

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 $p_o = 1$.[12] Household i of type $k(i)$ in location s receives indirect utility from purchasing life insurance from 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 with a large number of insurers implies type-specific residual demand curves facing insurer j in market s,[13]

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[12]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.

[13]With a small number of insurers, this demand system is a high-dimensional combinatorial problem that is not

16

$$Q_{js}^k\left(p_{js}, \kappa_{js}, P_s^k\right) = \iota_k \left(\frac{p_{js}}{P_s^k}\right)^{1-\varepsilon_k} \frac{E_s^k \kappa_{js}}{p_{js}}, \qquad P_s^k = \left(1 + \iota_k \sum_{j \in \mathcal{J}} \kappa_{js} p_{js}^{1-\varepsilon_k}\right)^{\frac{1}{1-\varepsilon_k}} \tag{8}$$

where $E_s^k = B_k \times \eta_s^k N_s$ are total expenditures by type k households across varieties in market s and B_k is the savings that type k households are choosing to allocate between the outside option and life insurance.[14] With preferences as in (7), the average welfare of a type k household in location s is B_k/P_s^k. Note that the market-type price index P_s^k 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 local household fundamentals $\{N_s, \{\eta_s^k\}\}_{s \in \mathcal{S}}$ and $\{B_k\}_{k=\ell,h}$ 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 $\{\iota_k, \varepsilon_k, B_k\}_{k=\ell,h}$, 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 $\{P_s^\ell, P_s^h\}_{s \in \mathcal{S}}$ 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.

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feasible to solve; however, the problem converges to (8) when $J \to \infty$.

[14]I set B_k to be 1.5% of type-k households' yearly wage, which corresponds to financial advisors' advice on optimal insurance coverage. I discuss this choice in more depth in Section 4.

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 $S_{js}^k \equiv p_{js}Q_{js}^k$ 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

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

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

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

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 Detroit, 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:
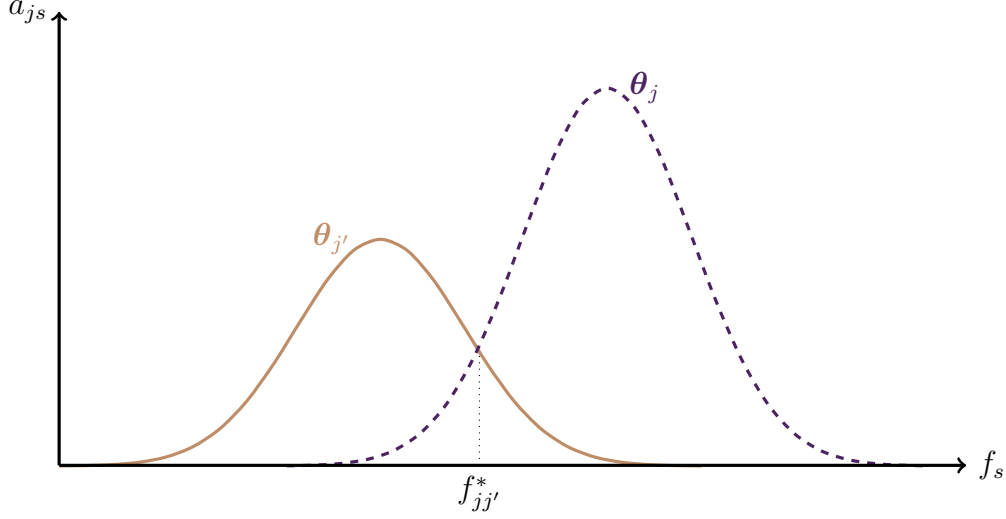
ASSUMPTION 1: INSURER TECHNOLOGY STRUCTURE

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 productivity. If Metlife devotes a larger amount of management time to advertising strategy, they have fewer managerial resources to devote to monitoring and training their agents.

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.

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 exist a threshold $f^*_{jj'}(\mathcal{P})$ 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 $f_s < f^*_{jj'}(\mathcal{P})$. Further:

1. *if $\mathcal{P} = \mathcal{P}^{flex}$, this threshold is unique;*

2. *if $\mathcal{P} = \mathcal{P}^{natl}$, this threshold is unique conditional on $\{P^h_s, P^\ell_s\}$.*

Proof: See Appendix A.2.

Proposition 2 is a result about spatial sorting. We can think of the unproductive insurer as Continental and the productive 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 productive. 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 local 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 η_s^h and is strictly increasing in η_s^h. Then $\mathbb{E}_j[\eta_s^h] > \mathbb{E}_{j'}[\eta_s^h]$, where

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

is insurer j's agent-weighted average local income.

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. Suppose further that f_s is only a function of η_s^h and is strictly increasing in η_s^h. Then under national 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.

FIGURE 2: THE EFFECT OF NATIONAL PRICING ON INSURER LOCATION DECISIONS
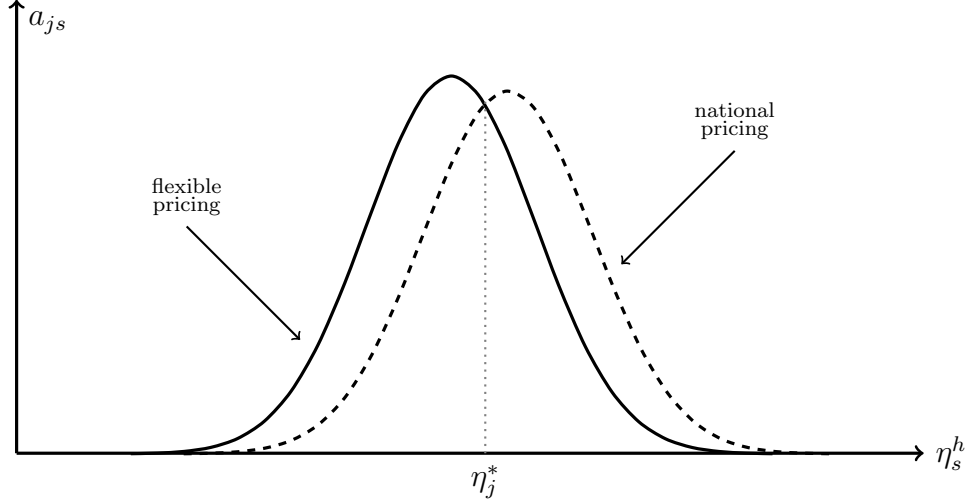
Note: This figure displays agent distributions across regulatory regimes for a given insurer. The cutoff η_j^{h*} corresponds to the respective local high-income shares in which the insurers place an equal number of agents across regimes. Solid lines correspond to the flexible pricing regime and dashed lines correspond to the uniform pricing regime. The figure is conditional on market size N_s.

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 $\iota \to \infty$, $\boldsymbol{\theta} \to \theta$, and f_s is solely a function of market size, $f_s = f(N_s)$, with $f'(N) > 0$. Then there exists a unique threshold schedule $\eta_j^{h*}(N)$ such that, conditional on N, $a_{js}^{\mathrm{natl}} < a_{js}^{\mathrm{flex}}$ if $\eta_s^h < \eta_j^{h*}(N)$ and $a_{js}^{\mathrm{natl}} > a_{js}^{\mathrm{flex}}$ if $\eta_s^h > \eta_j^{h*}(N)$.

Proof: See Appendix A.5.

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

$$\Delta \log \left(\frac{B_k}{P_s^k} \right) = \log P_s^{k,\text{flex}} - \log P_s^{k,\text{natl}}. \tag{13}$$

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

$$\Delta \log \left(\frac{B_k}{P_s^k} \right) \approx \frac{\iota_k}{\varepsilon_k - 1} \left[\underbrace{\sum_{j \in \mathcal{J}} \kappa_{js}^{\text{flex}} \left((p_{js}^{\text{natl}})^{1-\varepsilon_k} - (p_{js}^{\text{flex}})^{1-\varepsilon_k} \right)}_{\text{pricing margin effect}} + \underbrace{\sum_{j \in \mathcal{J}} \left(\kappa_{js}^{\text{natl}} - \kappa_{js}^{\text{flex}} \right) (p_{js}^{\text{natl}})^{1-\varepsilon_k}}_{\text{access margin effect}} \right]$$

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^{h*}, 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

23

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 $p_{js}^{\mathrm{natl}} < p_{js}^{\mathrm{flex}}$ and $\kappa_{js}^{\mathrm{natl}} < \kappa_{js}^{\mathrm{flex}}$ 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.[15] 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.[16]

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

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

---

[15]See Appendix B.5 for the counterpart to Proposition 1 when tax rates are heterogeneous across locations.

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

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, financial rating, return on equity, and an indicator for whether insurer j is a stock company. 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 constraint. 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 is not precisely estimated, but 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 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.4, 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.[17] 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.2, I also estimate the model using the results in column (1) and draw similar conclusions when conducting counterfactuals.

---

[17]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.

TABLE 3: DEMAND ESTIMATION RESULTS

	Variable Annuity Losses			Annuity Prices		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Price	−2.234	−3.154		−1.182	−0.304	
	(0.477)	(0.308)		(0.446)	(0.542)	
Log Price × $\tilde{\chi}_s$	−2.676	−2.045	−1.828	−2.882	−2.541	−2.701
	(0.055)	(0.055)	(0.032)	(0.000)	(0.000)	(0.000)
Size	0.809	0.686		0.375	0.427	
	(0.000)	(0.000)		(0.022)	(0.000)	
Rating	−1.420	−0.295		−1.703	−5.507	
	(0.431)	(0.845)		(0.582)	(0.000)	
Stock	−1.399	−0.688		0.583	0.737	
	(0.213)	(0.484)		(0.193)	(0.000)	
ROE	−1.149	−1.053		−0.308	−1.356	
	(0.006)	(0.026)		(0.852)	(0.031)	
Demand Controls	✓	✓		✓	✓	
Productivity Proxy		✓			✓	
Firm-Year FE			✓			✓
Agents				✓	✓	✓
Obs	11326	10784	12190	949	949	949
Within R^2	0.28	0.31	-0.01	0.29	0.75	0.09
F	105.0	111.4	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.

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 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.3.

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:

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

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:

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

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

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

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

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.

Finally, I set B_k to be 1.5% of type-k households' yearly wage. Financial advisors often recommend and ask their clients to purchase enough insurance to cover 10 times their yearly wage. To calculate the fraction of income they need to devote to yearly premiums, I first calculate the average premium in the Compulife data for a policy that pays out this amount. I then divide the average premium by the yearly wage. Since premiums scale approximately linearly for coverage large enough, this comes out to about 1.5% for both high- and low-income households.

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.2a 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

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.

implies that pricing margin welfare effects will be overestimated relative to access margin effects in small markets relative to large markets.

I then test how well the model can match the allocation of agents across commuting zones in a different time period. 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 series of exercises. First, I provide a methodology that converts welfare differences across locations into dollar amounts, and show how to decompose this measure into a pricing and access margin effect. Next, I document the margins driving spatial inequality under the flexible pricing regime, and show how national pricing affects both margins of inequality. I then consider how regulators can target the access margin explicitly through place-based tax policies. I wrap up with a discussion on robustness.

5.1   The Drivers of Spatial Inequality in the Life Insurance Industry

I evaluate spatial differences in welfare by computing compensating differentials. First, I select the commuting zone with the highest level of welfare under the flexible pricing regime. I refer to this location as the optimal commuting zone, and denote it as cz^*. I then compute the level of additional savings, $\hat{B}_{cz}^k$, necessary to equate welfare for each commuting zone cz to welfare in the optimal location cz^*, conditional on household type. I refer to $\hat{B}_{cz}^k$ as the compensating differential for type k households in commuting zone cz.

Given the welfare expression for the average household in location cz, B_k/P_{cz}^k, the compensating differential is implicitly defined by the relationship

$$\frac{B_k + \hat{B}_{cz}^k}{P_{cz}^k} = \frac{B_k}{P_{cz^*}^k}. \tag{17}$$

I also consider a counterfactual price index, $P_{cz}^{k,\text{price}}$, that holds fixed the allocation of agents in the optimal commuting zone and only considers changes in optimal markups across commuting zones.[18] The compensating differential for this counterfactual price index is then

$$\frac{B_k + \hat{B}_{cz}^{k,\text{price}}}{P_{cz}^{k,\text{price}}} = \frac{B_k}{P_{cz^*}^k}. \tag{18}$$

I refer to $\hat{B}_{cz}^{k,\text{price}}$ as the pricing margin of spatial inequality and refer to the difference in compensating differentials, $B_{cz}^k - \hat{B}_{cz}^{k,\text{price}}$, as the access margin of spatial inequality.

Figure 3 reports the compensating differential for each margin, averaged by commuting zone high-income population share deciles, for both low- and high-income households. Throughout this section, I focus the discussion on the bottom decile of local income. Low-income households in the bottom decile on average need to be given \$351 per year to be as well off as the average low-income household in the optimal commuting zone, and high-income households in the bottom decile need to be given \$506 per year. In percentage terms, low-income households need to be given 0.95% of their yearly income, while high-income households need to be given 0.41% of their yearly income.

The access margin of spatial inequality is large relative to the pricing margin. The pricing margin only reflects 5.7% of the compensating differential (\$20 per year) for low-income households, and 18.2% (\$92 per year) for high-income households. The remainder is attributed to differential access, which in welfare terms includes both the general availability of insurers as well as differences in the quality of insurers relative to the optimal commuting zone.

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[18]This counterfactual price index is calculated as

$$P_{cz}^{k,\text{price}} = \left(1 + \iota_k \sum_{j \in \mathcal{J}} \omega_j \kappa_{j,cz^*} p_{j,cz}^{1-\varepsilon_k}\right)^{\frac{1}{1-\varepsilon_k}}$$

FIGURE 3: COMPENSATING DIFFERENTIALS UNDER FLEXIBLE PRICING
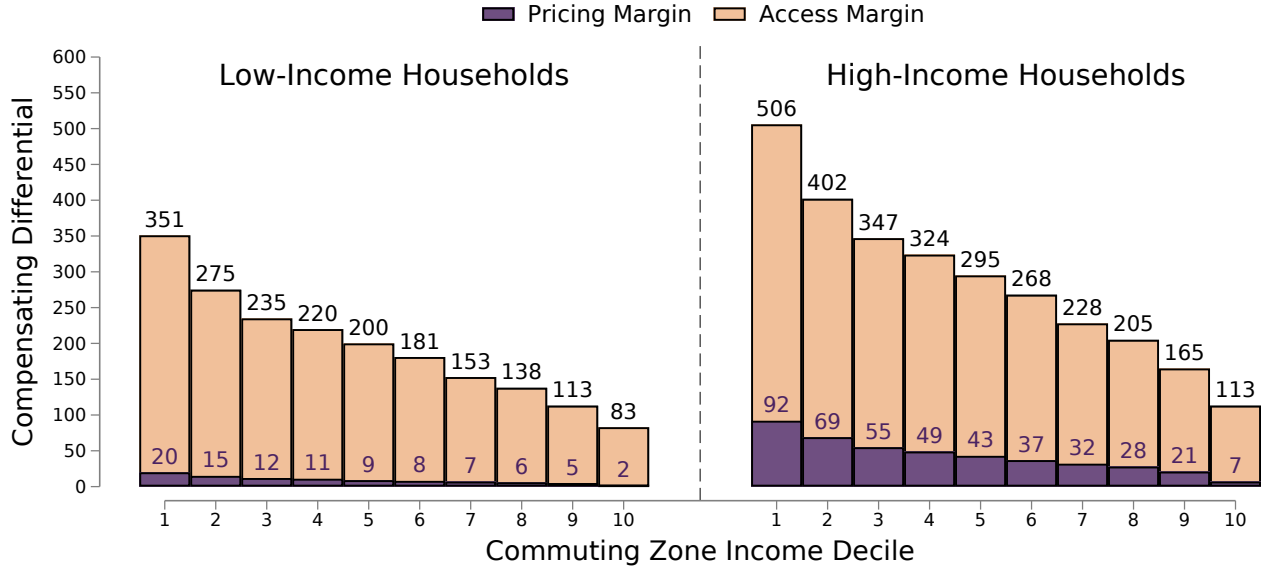
Note: This figure reports compensating differentials across commuting zone high-income population share deciles. Dark purple bars reflect the pricing margin, while the light tan bars reflect the access margin. The pricing margin values are reported in purple above the purple bars, and the total differentials are reported in black above each bar. I condition on low-income households in the left section and high-income households in the right section.

These estimates are comparable to other estimates of under-diversification in the literature. For example, Calvet et al. (2007) find that under-diversification in stock market equity leads to losses of around 0.5% of lifetime income, and Koijen et al. (2016) find that deviations in optimal health and life insurance coverage leads to losses of 3.2% of lifetime income. The similar magnitudes suggest that part of what drives sub-optimal investment choices is differences in accessible investment options across geographic regions.[19]

5.2 THE EFFECTS OF NATIONAL PRICING ON SPATIAL INEQUALITY

I now use the model to analyze the effects of national pricing on spatial inequality. 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.

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[19]These comparisons have two caveats: first, both of these studies consider dynamic frameworks and compare to lifetime income, while this paper works in a static environment. However, if the effects are persistent over time, these two measures should coincide. Second, both papers consider deviations in observed choices to a model-implied optimal portfolio choice. Here, I'm comparing each commuting zone to the optimal location and do not account for mistakes in optimal insurance participation. It is therefore likely that the compensating differentials would be much larger if I conducted the same experiment.

FIGURE 4: THE EFFECT OF UNIFORM PRICING REGULATION ON FIRM DECISIONS

(a) Log Prices

(b) Market Penetration
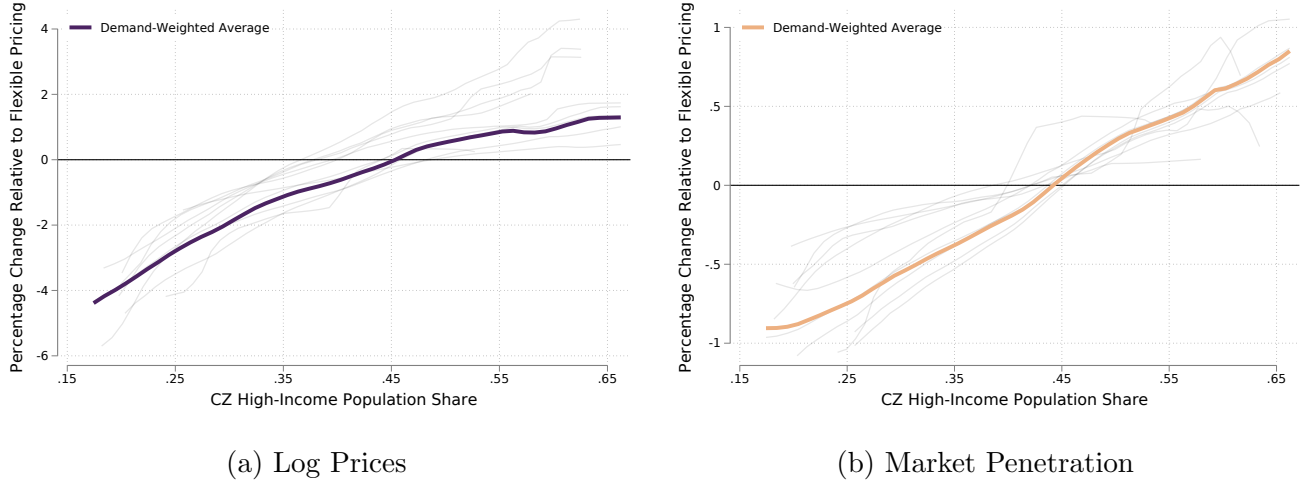
Note: This figure compares equilibrium insurer decisions under national pricing restrictions relative to flexible pricing. Each subfigure plots the decisions for each of the ten deciles of insurers as well as a demand-component-weighted average of the responses. All lines are local polynomials estimated 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.

Both figures are consistent with the description 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.

I next compute compensating differentials as in Section 5.1 but under national pricing regulation. By definition, national pricing eliminates the pricing margin of spatial inequality: if cz has access to the same insurers as cz^*, then under national pricing, $p_{j,cz} = p_{j,cz^*}$ for all active j. Differences in spatial inequality across regulatory regimes are therefore driven by changes in the access margin.

Figure 5 reports the results. The access margin effects offset the effects of the pricing margin for low-income households, but dampen them for high-income households. Taken together, national pricing increases spatial inequality for low-income households but reduces it for high-income households. These between-type differences are related to Proposition 5 in Section 3.5: low-income households, having lower price elasticities, are relatively more sensitive to the access margin than high-income households.

The results imply that national pricing, while alleviating pricing inequality, does not necessarily make low-income households better off relative to the optimal location. Further, the decomposition
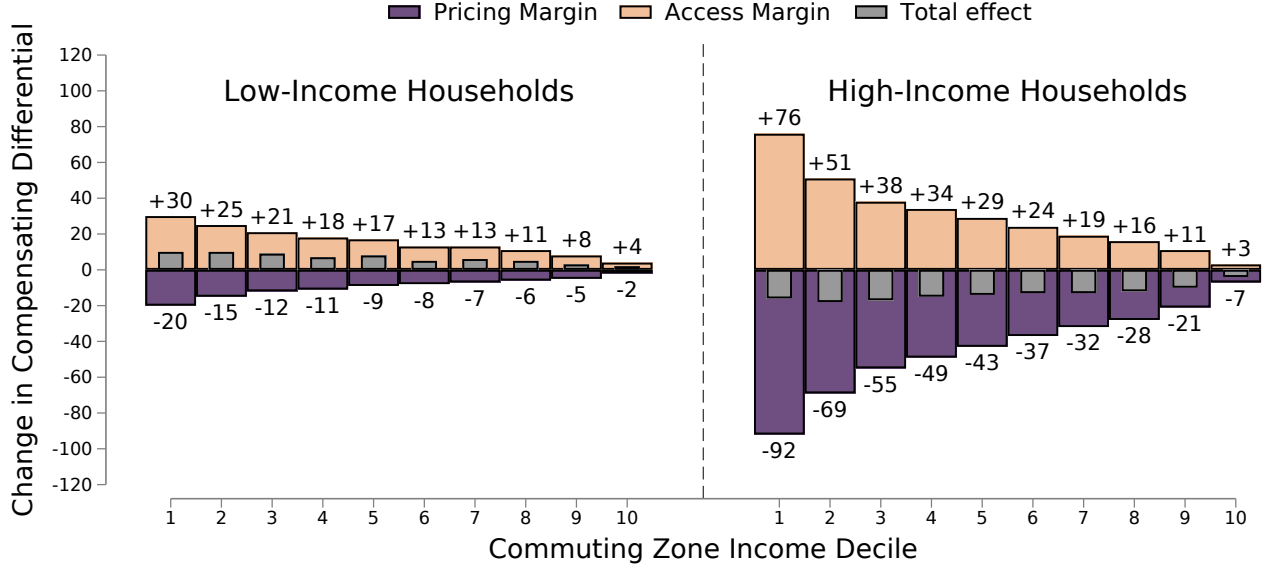
Note: This figure reports the effects of national pricing on compensating differentials relative to flexible pricing across commuting zone high-income population share deciles. Dark purple bars reflect the pricing margin, while the light tan bars reflect the access margin. I condition on low-income households in the left section and high-income households in the right section.

in Figure 3 suggests that the returns to targeting the access margin should outweigh the returns of targeting the pricing margin. I now turn to a policy that does just that.

## 5.3 A COMPLEMENTARY PLACE-BASED TAX POLICY

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

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

$$\sum_{s \in \mathcal{S}} \sum_{j \in \mathcal{J}} t_s^* S_{js}^* = \sum_{s \in \mathcal{S}} \sum_{j \in \mathcal{J}} t_s S_{js}^{\mathrm{natl}}.$$

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
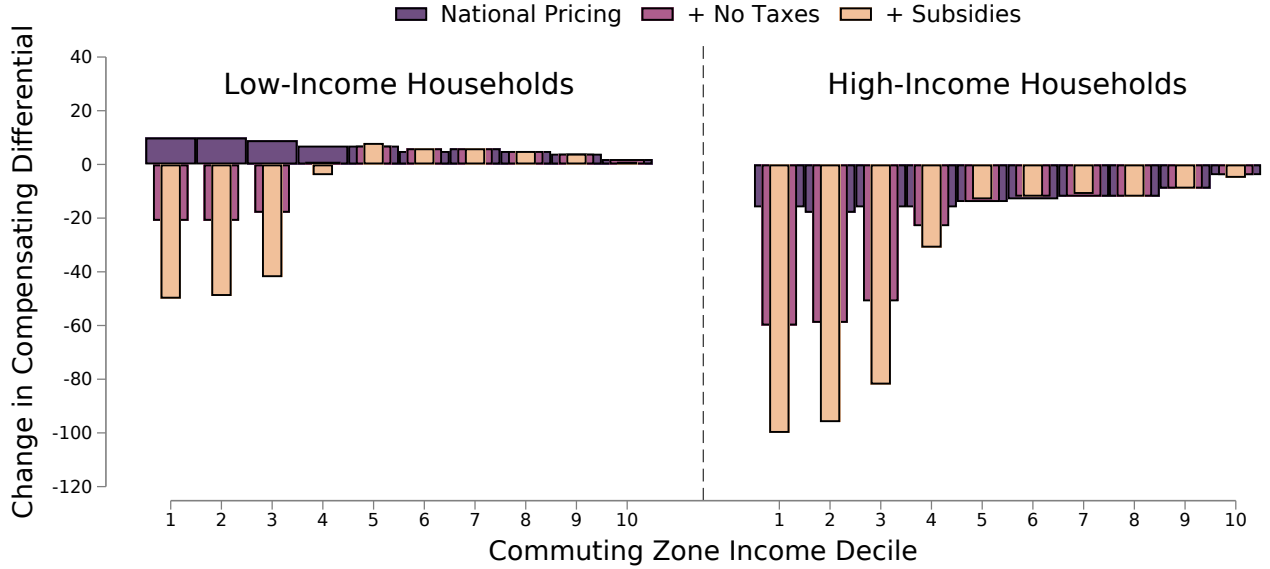
Note: This figure reports the effects of the place-based policies on compensating differentials relative to flexible pricing across commuting zone high-income population share deciles. Dark purple bars show the effects of national pricing by itself. Pink bars reflect the additional effects of the no-tax policy, while the light tan bars reflect the additional effects of the subsidy policy. I condition on low-income households in the left section and high-income households in the right section.

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 commuting zones. For example, if a commuting zone has an observed tax rate of 2%, I replace the tax with a subsidy of 2%. I again offset the tax revenue losses by increasing tax rates in the richer commuting zones.

Figure 6 reports the effects on spatial inequality for each policy. The figure also includes the effects of national pricing alone for reference. The poorest commuting zones see a strong reduction in their compensating differentials: the no-tax policy is equivalent to giving $20 per year to low-income households in the poorest decile and $60 per year to high-income households in the poorest decile. The policy scales almost linearly: the subsidy policy is equivalent to giving $50 per year to low-income households and $100 per year to high-income households in the poorest decile of commuting zones.

Importantly, the gains in the poor commuting zones do not result in substantial losses for households in the richer commuting zones. For example, in the fifth decile of commuting zone income, national pricing increases the compensating differential for low-income households by $7 per year, and the subsidy policy further increases this by only $1 per year. The policies therefore do not substantially increase inequality in the middle of the distribution, but have strong effects at the bottom of the distribution.

5.4 The Effects of National Pricing at the Local Level

The analysis in Sections 5.1-5.3 focuses on spatial inequality. However, more spatial inequality does not necessarily mean that households are worse off in these locations. For example, it may be that national pricing makes low-income households better off in a commuting zone, but less so than the optimal commuting zone, leading to more spatial inequality.

In Appendix E.1, I analyze the effects of national pricing on welfare relative to the flexible pricing benchmark within a commuting zone. In other words, compared to flexible pricing, are low-income households in Detroit better or worse off under national pricing? Are the effects similar for high-income households or for households in New York City?

I focus the discussion on low-income households but include results for high-income households in the appendix. I find that low-income households are worse off on average in each of the bottom nine deciles of commuting zone income and better off in the top decile. For example, in the poorest decile, national pricing reduces compensating differentials on the pricing margin by $2.90, but increases compensating differentials on the access margin by $6.30. In the richest decile, low-income households are better off by $3 on the access margin, but worse off by $1.50 on the pricing margin.

The results imply that national pricing increases spatial inequality both by making households in poor commuting zones worse off and by making households in the richest commuting zones better off. This bolsters the motivation for place-based policies since they explicitly target the commuting zones that fare the worst.

5.5 Robustness to Alternative Elasticity Estimates

The estimates in Sections 5.1-5.3 use the elasticity estimates from the Hausman et al. (1994)-style annuity price instrument. However, these elasticity estimates are small relative to the estimates using variable annuity losses, which could affect the magnitudes of the counterfactual estimates. I therefore re-estimate the model with the variable annuity estimates in Section E.2 and compare the results to the benchmark.

Larger elasticities reduce the magnitudes of spatial inequality as measured through compensating differentials. For example, using the variable annuity losses elasticities, low-income households in the poorest decile of commuting zones need to be given $153 per year to equate their welfare to the optimal location as opposed to $351 in the benchmark, a reduction of about 58%. However, the relative effects between margins are similar: the access margin accounts for 92.8% of the compensating differential under the VA losses estimates compared to 94.3% under the Hausman et al. (1994) instrument.

Further, place-based tax policies have similar effects on welfare across instruments. Using the variable annuity losses instrument, the subsidy policy reduces compensating differentials relative

to flexible pricing by 20-25% in the poorest third of commuting zones, depending on the income decile. This percentage reduction is greater than the benchmark estimates in which compensating differentials decline by 15-20%.

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 a small number of firms as in Atkeson and Burstein (2008), as I use the results in Appendix B.7 below. To revert back to the large number of firms 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 insurer j take the form

$$
\pi_{js} = (p_{js} - \xi)\left(Q_{js}^h + Q_{js}^\ell\right)
$$
$$
= (p_{js} - \xi)\left\{\iota_h \frac{\kappa_{js}E_s^k}{p_{js}}\left(\frac{p_{js}}{P_s^h}\right)^{1-\varepsilon_h} + \iota_\ell \frac{\kappa_{js}E_s^\ell}{p_{js}}\left(\frac{p_{js}}{P_s^\ell}\right)^{1-\varepsilon_\ell}\right\}.
$$

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

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

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

$$
\frac{\kappa_{js}p_{js}^{1-\varepsilon_k}}{(P_s^k)^{1-\varepsilon_k}} = \frac{\iota_k\kappa_{js}p_{js}^{1-\varepsilon_k}}{1 + \sum_{j'}\iota_k\kappa_{j's}p_{j's}^{1-\varepsilon_k}}
$$
$$
= \frac{p_{js}[\iota_k\kappa_{js}E_s^k/(p_{js}(P_s^k)^{1-\varepsilon_k})]p_{js}^{1-\varepsilon_k}}{E_s^k/(P_s^k)^{1-\varepsilon_k} + \sum_{j'}p_{j's}[\iota_k\kappa_{j's}E_s^k/(p_{j's}(P_s^k)^{1-\varepsilon_k})]p_{j's}^{1-\varepsilon_k}}
$$
$$
= \frac{p_{js}Q_{js}^k}{p_o Q_{os}^k + \sum_{j'}p_{j's}Q_{j's}^k}
$$
$$
= \sigma_{js}^k.
$$

It follows that we can rewrite the first order condition as

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

Define the within-market-income elasticity, $\varepsilon_{js}^k = (1 - \sigma_{js}^k)\varepsilon_k + \sigma_{js}^k$, and the high-income within-market sales share, $\delta_{js}^{\text{wh}} = Q_{js}^h/(Q_{js}^h + Q_{js}^\ell)$. Dividing both sides by $Q_{js}^h + Q_{js}^\ell$, we can now write

$$
1 - \left(\frac{p_{js}-\xi}{p_{js}}\right)\left[\delta_{js}^{\text{wh}}\varepsilon_{js}^h + (1-\delta_{js}^{\text{wh}})\varepsilon_{js}^\ell\right] = 1 - \left(\frac{p_{js}-\xi}{p_{js}}\right)\Delta_{js} = 0
$$

where $\Delta_{js} \equiv \sigma_{js}^k + (1 - \sigma_{js}^k)\varepsilon_k$. 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 when $\sigma_{js}^k = 0$. Turning to the natlorm pricing case, note that the first order condition is just the sum of the derivatives of each local profit function,

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

Multiplying and dividing through by p_j and dividing through by $\sum_s (Q_{js}^h + Q_{js}^\ell)$, we can now write

$$\sum_{s \in \mathcal{S}} \left(\frac{p_j(Q_{js}^h + Q_{js}^\ell)}{\sum_{s'} p_j(Q_{js'}^h + Q_{js'}^\ell)}\right) \left\{ 1 - \left(\frac{p_j - \xi}{p_j}\right)\Delta_{js} \right\} = 1 - \left(\frac{p_j - \xi}{p_j}\right) \sum_{s \in \mathcal{S}} \delta_{js}^b \Delta_{js} = 0.$$

Once again solving for p_j, we get the familiar formula

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

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 natlorm 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 $A_{js}, A_{j's} > 0$,

$$\frac{\kappa_A(A_{js}, N_s)}{\kappa_A(A_{js}, N_s)} = \frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}}. \tag{A.2.1}$$

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 (A.2.1), 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. $\qquad\square$

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 (A.2.1) 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 $f_s > f^*(j, j')$. $\qquad\square$

CASE 2: UNIFORM PRICING

For the natlorm 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

$$\Omega_s = \frac{\Phi_s(p_{j'})}{\Phi_s(p_j)} = \frac{(p_{j'} - \xi)p_{j'}^{-\varepsilon_\ell}}{(p_j - \xi)p_j^{-\varepsilon_\ell}} \left[\frac{1 + \chi_s(\mathcal{R}_s p_{j'}^{\varepsilon_\ell - \varepsilon_h} - 1)}{1 + \chi_s(\mathcal{R}_s p_j^{\varepsilon_\ell - \varepsilon_h} - 1)} \right], \qquad \mathcal{R}_s \equiv \frac{(P_s^h)^{1-\varepsilon_h}}{(P_s^\ell)^{1-\varepsilon_\ell}}.$$

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. *If $p_j < p_{j'}$, then $\Omega_s(p_j, p_{j'}) > 1$ when $\chi_s = 0$ and $\Omega_s(p_j, p_{j'}) < 1$ when $\chi_s = 1$*

2. *Ω_s is decreasing in χ_s and $\mathcal{R}_s$.*

Proof: 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 $p_h = (1 - \varepsilon_h^{-1})^{-1}\xi$. Since $p_j < p_{j'}$, we therefore have $p_h < p_j < p_{j'} < p_\ell$. Hence, $\Omega_s > 1$ when $\chi_s = 0$ and $\Omega_s < 1$ when $\chi_s = 1$.

It remains to show that Ω_s is decreasing in χ_s and $\mathcal{R}_s$. First, fix $\mathcal{R}_s$. Differentiating with

respect to χ_s, we have

$$\frac{\partial \Omega_s}{\partial \chi_s} \propto (\mathcal{R}_s p_{j'}^{\varepsilon_\ell - \varepsilon_h} - 1)[1 + \chi_s(\mathcal{R}_s p_j^{\varepsilon_\ell - \varepsilon_h} - 1)] - (\mathcal{R}_s p_j^{\varepsilon_\ell - \varepsilon_h} - 1)[1 + \chi_s(\mathcal{R}_s p_{j'}^{\varepsilon_\ell - \varepsilon_h} - 1)]$$

$$= \mathcal{R}_s(p_{j'}^{\varepsilon_\ell - \varepsilon_h} - p_j^{\varepsilon_\ell - \varepsilon_h}) < 0.$$

Since this holds for any $\mathcal{R}_s$, it must be that Ω_s is strictly decreasing in χ_s. Next, fix χ_s. In similar fashion, we have

$$\frac{\partial \Omega_s}{\partial \mathcal{R}_s} \propto \chi_s p_{j'}^{\varepsilon_\ell - \varepsilon_h}[1 + \chi_s(\mathcal{R}_s p_j^{\varepsilon_h - \varepsilon_\ell} - 1)] - \chi_s p_j^{\varepsilon_\ell - \varepsilon_h}[1 + \chi_s(\mathcal{R}_s p_{j'}^{\varepsilon_\ell - \varepsilon_h} - 1)]$$

$$= \chi_s(1 - \chi_s)(p_{j'}^{\varepsilon_\ell - \varepsilon_h} - p_j^{\varepsilon_\ell - \varepsilon_h}) < 0$$

as long as $\chi_s \in (0,1)$. This completes the proof. $\qquad\square$

It's now useful to note that the first-order condition (A.2.1) becomes

$$\frac{\kappa_A(A_{js}, N_s)}{\kappa_A(A_{js}, N_s)} = \Omega_s\left(\frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}}\right). \tag{A.2.2}$$

With this in mind, I first prove the following claim.

Claim 1: *There exists an $f^* \in (0, \infty)$ such that $A_{js} = A_{j's}$.*

To prove the claim, suppose by way of contradiction that $A_{js} > A_{j's}$ for all s. Then it follows that $\lambda_j > \lambda_{j'}$. But this also implies

$$\lim_{f_s \to 0} \lim_{\chi_s \to 0} \Omega_s\left(\frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}}\right) = \lim_{\chi_s \to 0} \Omega_s\left(\frac{\lambda_j}{\lambda_{j'}}\right) > 1$$

since $\Omega_s > 1$ by Lemma A.2.2. From the first order condition (A.2.2), it must be that for locations such that $f_s \to 0$ and $\chi_s \to 0$, $A_{js} < A_{j's}$. But this is a contradiction, so it must be that $A_{js} < A_{j's}$ for some s.

Similarly, suppose $A_{js} < A_{j's}$ for all s. Then we have

$$\lim_{f_s \to \infty} \lim_{\chi_s \to 1} \Omega_s\left(\frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}}\right) = \lim_{\chi_s \to 1} \Omega_s\left(\frac{\theta_{j'}}{\theta_j}\right) < 1.$$

which follows from the fact that $\theta_j > \theta_{j'}$ and $\Omega_s < 1$ by Lemma A.2.2. But this implies that in these locations, $A_{js} > A_{j's}$, which is again a contradiction. Therefore, there exist locations in which $A_{js} < A_{j's}$ and $A_{js} > A_{j's}$. Continuity implies the existence of a f^* for some pair of fundamentals (χ^*, N^*) such that $A_{js} = A_{j's}$. $\qquad\square$

Order j such that $j > j'$ if $p_j < p_{j'}$. Consider an allocation of agents $\{A_{js}\}_j$ for some location with χ_s and N_s and such that $A_{js} = A_{j's}$. Suppose $\Omega_{s'} > \Omega_s$ when $\chi_{s'} > \chi_s$ for some $\chi_{s'}$ close to χ_s. Then if $f_s = f_{s'}$ and $N_s = N_{s'}$, we have

$$\frac{\kappa_A(A_{js}, N_s)}{\kappa_A(A_{j's}, N_s)} = \Omega_s \left(\frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}} \right) < \Omega_{s'} \left(\frac{f_s/\theta_j + \lambda_j}{f_s/\theta_{j'} + \lambda_{j'}} \right) = \frac{\kappa_A(A_{js'}, N_s)}{\kappa_A(A_{j's'}, N_s)}.$$

It follows that since $A_{js} = A_{j's}$, it must be that $A_{js'} < A_{j's'}$, and therefore, $\kappa_{js} < \kappa_{j's}$. Further, note that

$$\frac{d\Omega_s}{d\chi_s} = \frac{\partial\Omega_s}{\partial\chi_s} + \frac{\partial\Omega_s}{\partial\mathcal{R}_s}\frac{\partial\mathcal{R}_s}{\partial\chi_s} \propto \left[\mathcal{R}_s + \chi_s(1-\chi_s)\frac{\partial\mathcal{R}_s}{\partial\chi_s} \right] (p_{j'}^{\varepsilon_\ell-\varepsilon_h} - p_j^{\varepsilon_\ell-\varepsilon_h}) > 0$$

must hold for all pairs j and j' such that $p_j < p_{j'}$ since it holds for the two given firms.

Note that since $\{\iota_h, \iota_\ell\} \to \infty$, we can write

$$\mathcal{R}_s = \sum_{j\in\mathcal{J}} \tilde{\kappa}_{js}p_j^{1-\varepsilon_\ell} \Big/ \sum_{j\in\mathcal{J}} \tilde{\kappa}_{js}p_j^{1-\varepsilon_h}, \qquad \tilde{\kappa}_{js} \equiv \frac{\kappa_{js}}{\sum_j \kappa_{js}}.$$

Next, I need the following lemma. [In progress.]

A.3 Proof of Corollary 2.1

First, condition on $x = \{P_s^h, P_s^\ell\}$. Then by Proposition 2, there exists an $f_{jj'}^*(x)$ such that $A_{js} < A_{j's}$ if $f_s < f_{jj'}^*(x)$ and $A_{js} > A_{j's}$ if $f_s > f_{jj'}^*(x)$. Define

$$\mathbb{E}_j[\eta_s^h|x] = \sum_{s\in\mathcal{S}} \left(\frac{A_{js}(x)}{\sum_{s'} A_{js'}(x)} \right) \eta_s^h = \sum_{s\in\mathcal{S}} \left(\frac{a_{js}(x)}{\sum_{s'} a_{js'}(x)} \right) \eta_s^h$$

Next, define $\rho_j(x) = \sum_{s:f_s<f_{jj'}^*(x)} a_{js} / \sum_s a_{js}$. It follows that

$$\begin{aligned}
\mathbb{E}_j[\eta_s^h|x] &= \rho_j(x)\mathbb{E}_j[\eta_s^h|x, f_s < f_{jj'}^*(x)] + (1-\rho_j(x))\mathbb{E}_j[\eta_s^h|x, f_s \geq f_{jj'}^*(x)] \\
&\geq \rho_{j'}(x)\mathbb{E}_{j'}[\eta_s^h|x, f_s < f_{jj'}^*(x)] + (1-\rho_{j'}(x))\mathbb{E}_{j'}[\eta_s^h|x, f_s \geq f_{jj'}^*(x)] \\
&= \mathbb{E}_j[\eta_s^h|x]
\end{aligned}$$

since $\rho_j(x) \leq \rho_{j'}(x)$. It therefore follows from here that

$$\mathbb{E}_j[\eta_s^h] = \sum_x \left(\frac{\sum_{s|x} a_{js}(x)}{\sum_s a_{js}} \right) \mathbb{E}_j[\eta_s^h|x] \geq \sum_x \left(\frac{\sum_{s|x} a_{j's}(x)}{\sum_s a_{j's}} \right) \mathbb{E}_{j'}[\eta_s^h|x] = \mathbb{E}_{j'}[\eta_s^h]$$

as desired. □

A.4   Proof of Corollary 2.2

This proof follows from the fact that δ_{js} is ordered the same as $a_{js}/\sum_s a_{js'}$ and the proof of the previous corollary. □

A.5   Proof of Proposition 3

First note that when $\iota \to 0$ and $\boldsymbol{\theta} \to \theta$, $p_j^{\text{natl}} = p_{j'}^{\text{natl}}$ for all and j and $\tilde{\kappa}_{js} = \tilde{\kappa}_{j's}$ for all j and s. Therefore,

$$\left(\frac{p_j^{\text{natl}}}{P_s^{k,\text{natl}}}\right)^{1-\varepsilon_k} = \frac{(p_j^{\text{natl}})^{1-\varepsilon_k}}{\sum_{j\in\mathcal{J}} \tilde{\kappa}_{j's}(p_{j'}^{\text{natl}})^{1-\varepsilon_k}} = \frac{1}{J\tilde{\kappa}_{js}}.$$

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

$$\frac{\Phi_{js}^{\text{natl}}(p_j)}{\Phi_{js}^{\text{flex}}(p_{js})} = \left(\frac{1-\xi/p_j^{\text{natl}}}{1-\xi/p_{js}^{\text{flex}}}\right)\left(\frac{\sum_k E_s^k(p_j^{\text{natl}}/P_s^{k,\text{natl}})^{1-\varepsilon_k}}{\sum_k E_s^k(p_{js}^{\text{flex}}/P_s^{k,\text{flex}})^{1-\varepsilon_k}}\right) = \frac{\Delta_{js}}{\zeta_j}\frac{\tilde{\kappa}_{js}^{\text{flex}}}{\tilde{\kappa}_{js}^{\text{natl}}}, \tag{A.5.1}$$

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 insurers are identical by assumption, the remainder of the proof drops the j subscript from all insurer-specific variables. I also drop the subscript on N_s since I condition on population.

Conditional on being active in a location s under both regimes, we can take logs of the agent optimality condition (12) and write

$$-\Delta\log\left(\frac{\tilde{\kappa}_A(A_s,N)}{\tilde{\kappa}(A_s,N)}\right) = \Delta\log\left(\frac{\Delta_s}{\zeta}\right) - \Delta\log(f_s/\theta + \lambda_j). \tag{A.5.2}$$

where I define $\Delta x \equiv x^{\text{natl}} - x^{\text{flex}}$ for a given variable x and $\lambda = \widetilde{C}'(\bar{A})$. 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. It will also be useful to note that $-\Delta(\tilde{\kappa}_A(A_s,N)/\tilde{\kappa}(A_s,N)) > 0$ if and only if $\Delta A_s > 0$.

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 $\Delta A_s > 0$ for all s, so that $-\Delta(\tilde{\kappa}_A(A_s,N)/\tilde{\kappa}(A_s,N)) > 0$ for all s. Let $\underline{\Delta}$ and $\bar{\Delta}$ be the optimal flexible pricing elasticities for the smallest and largest values of

η_s^h, respectively. Then since $\Phi_s^{\text{natl}} = 1/(\zeta \tilde{\kappa}_s^{\text{natl}})$, there are no locations with $A_s = 0$, implying that $\zeta \in (\underline{\Delta}, \bar{\Delta})$. For $\eta_s^h \to 0$, we therefore have $\Delta_s < \zeta$.

From the assumption that $\Delta A_s > 0$ for all s, it follows that $\lambda^{\text{natl}} > \lambda^{\text{flex}}$; thus, $\Delta \log(f_s/\theta + \lambda_j) > 0$. Therefore, as $\eta_s^h \to \underline{\eta}^h$, we have

$$-\Delta \log\left(\frac{\tilde{\kappa}_A(A_s, N)}{\tilde{\kappa}(A_s, N)}\right) = \Delta \log\left(\frac{\Delta_s}{\zeta}\right) - \Delta \log(f_s/\theta + \lambda_j) < 0 < -\Delta \log\left(\frac{\tilde{\kappa}_A(A_s, N)}{\tilde{\kappa}(A_s, N)}\right)$$

where the last inequality follows from the assumption that $\Delta A_s > 0$. 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 $\Delta A_s < 0$ for all locations so the left-hand side of (A.5.2) is negative. It follows that $\Delta \lambda < 0$, implying $\Delta \log(f_s/\theta + \lambda) < 0$. It follows that for $\eta_s^h \to \bar{\eta}^h$, $\Delta_s > \zeta$, so

$$-\Delta \log\left(\frac{\tilde{\kappa}_A(A_s, N)}{\tilde{\kappa}(A_s, N)}\right) = \Delta \log\left(\frac{\Delta_s}{\zeta}\right) - \Delta \log(f_s/\theta + \lambda_j) > 0 > -\Delta \log\left(\frac{\tilde{\kappa}_A(A_s, N)}{\tilde{\kappa}(A_s, N)}\right)$$

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 strictly increasing in η_s^h conditional on market size.*

Note that conditional on N_s, $\log(f_s/\theta + \lambda) = \log(f_{s'}/\theta + \lambda)$ since $f_s = f(N_s) = f(N_{s'}) = f_{s'}$ for any two $s, s' \in \mathcal{S}$. Suppose $\eta_s^h > \eta_{s'}^h$, so $\Delta_s > \Delta_{s'}$. It follows that

$$\left[-\Delta \log\left(\frac{\tilde{\kappa}_A(A_s, N)}{\tilde{\kappa}(A_s, N)}\right)\right] - \left[-\Delta \log\left(\frac{\tilde{\kappa}_A(A_{s'}, N)}{\tilde{\kappa}(A_{s'}, N)}\right)\right] = \log\left(\frac{\Delta_s}{\Delta_{s'}}\right) > 0$$

which implies $\Delta A_s > \Delta A_{s'}$. $\square$

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

$$\log(P_s^k) = \frac{1}{1 - \varepsilon_k} \log \left(1 + \iota_k \sum_{j \in \mathcal{J}} \kappa_{js} p_{js}^{1-\varepsilon_k} \right)$$

$$\approx -\frac{\iota_k}{\varepsilon_k - 1} \sum_{j \in \mathcal{J}} \kappa_{js} p_{js}^{1-\varepsilon_k}$$

where the second line follows using the first-order approximation $\log(1 + x) \approx x$. It follows by substituting this into the expression for $\Delta \mathbb{W}_s^k$ that

$$\Delta \log \mathbb{W}_s^k \approx \left[-\frac{\iota_k}{\varepsilon_k - 1} \sum_{j \in \mathcal{J}} \kappa_{js}^{\text{flex}} (p_{js}^{\text{flex}})^{1-\varepsilon_k} \right] - \left[-\frac{\iota_k}{\varepsilon_k - 1} \sum_{j \in \mathcal{J}} \kappa_{js}^{\text{natl}} (p_{js}^{\text{natl}})^{1-\varepsilon_k} \right]$$

$$= \frac{\iota_k}{\varepsilon_k - 1} \left[\sum_{j \in \mathcal{J}} \kappa_{js}^{\text{natl}} (p_{js}^{\text{natl}})^{1-\varepsilon_k} - \sum_{j \in \mathcal{J}} \kappa_{js}^{\text{flex}} (p_{js}^{\text{flex}})^{1-\varepsilon_k} \right]$$

$$= \frac{\iota_k}{\varepsilon_k - 1} \left[\sum_{j \in \mathcal{J}} \kappa_{js}^{\text{natl}} (p_{js}^{\text{natl}})^{1-\varepsilon_k} + \left(\sum_{j \in \mathcal{J}} \kappa_{js}^{\text{natl}} (p_{js}^{\text{flex}})^{1-\varepsilon_k} - \sum_{j \in \mathcal{J}} \kappa_{js}^{\text{natl}} (p_{js}^{\text{flex}})^{1-\varepsilon_k} \right) - \sum_{j \in \mathcal{J}} \kappa_{js}^{\text{flex}} (p_{js}^{\text{flex}})^{1-\varepsilon_k} \right]$$

$$= \frac{\iota_k}{\varepsilon_k - 1} \left[\sum_{j \in \mathcal{J}} \kappa_{js}^{\text{natl}} \left((p_{js}^{\text{natl}})^{1-\varepsilon_k} - (p_{js}^{\text{flex}})^{1-\varepsilon_k} \right) + \sum_{j \in \mathcal{J}} \left(\kappa_{js}^{\text{natl}} - \kappa_{js}^{\text{flex}} \right) (p_{js}^{\text{flex}})^{1-\varepsilon_k} \right].$$

This completes the proof. □

A.7 Proof of Proposition 5

This proof follows from rewriting the expression for each individual insurer's component of the log change in welfare, namely

$$\kappa_{js}^{\text{natl}} \left((p_j^{\text{natl}})^{1-\varepsilon_k} - (p_{js}^{\text{flex}})^{1-\varepsilon_i} \right) = \kappa_{js}^{\text{natl}} (p_{js}^{\text{ptm}})^{1-\varepsilon_m} \left[\left(\frac{p_{js}^{\text{ptm}}}{p_{js}^{\text{natl}}} \right)^{\varepsilon_m - 1} - \frac{\kappa_{js}^{\text{ptm}}}{\kappa_{js}^{\text{natl}}} \right].$$

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

Under this case, it's clear that $(p_{js}^{\text{ptm}}/p_{js}^{\text{natl}})^{\varepsilon_m - 1}$ 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 κ_{js} 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 $(p_{js}^{\mathrm{ptm}}/p_{js}^{\mathrm{natl}})^{\varepsilon_m-1} = 1$, and so the sign of the bracketed term is simply $\mathrm{sgn}(\kappa_{js}^{\mathrm{natl}} - \kappa_{js}^{\mathrm{ptm}}) = -1$. On the other hand, note that with $p_{js}^{\mathrm{ptm}} > p_{js}^{\mathrm{natl}}$, 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. $\qquad\square$

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

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

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:

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

B.3 INTERPRETING DEMAND AS RELATIVE TO ACTUARIAL VALUE

This section shows how to reinterpret the theoretical model using actuarial values. Starting with demand, note that we can instead write the life insurance values ι_k as

$$\log \iota_k = \log \tilde{\iota}_k + (\varepsilon_k - 1)\log v,$$

where v is the actuarially fair value of a life insurance policy defined in Section 2 and $\tilde{\iota}_k$ is the residual. In this case, the residual demand curves can be written

$$Q_s^k(p_{js}, \kappa_{js}, P_s^k) = \tilde{\iota}_k \left(\frac{p_{js}/v}{P_s^k}\right)^{1-\varepsilon_k} \frac{E_s^k \kappa_{js}}{p_{js}}.$$

Next, since v is essentially the expected payouts net of returns, write $\xi = \tilde{\xi}v$, where $\tilde{\xi}$ is now interpreted as the cost markup over fair value. Substituting this demand curve into firm j's profit expression, we have

$$\pi_{js} = (p_{js} - \tilde{\xi}v) \sum_k \tilde{\iota}_k \left(\frac{p_{js}/v}{P_s^k}\right)^{1-\varepsilon_k} \frac{E_s^k \kappa_{js}}{p_{js}} - f_s a_{js}$$

$$= \left(\frac{p_{js}}{v} - \tilde{\xi}\right) \sum_k \tilde{\iota}_k \left(\frac{p_{js}/v}{P_s^k}\right)^{1-\varepsilon_k} \frac{E_s^k \kappa_{js}}{p_{js}/v} - f_s a_{js}.$$

Relabeling $\tilde{p}_{js} \equiv p_{js}/v$, we are back to the original problem.

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

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

54

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:

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

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, there may be differences in tax rates across locations, or perhaps some locations have drastically different mortality rates for reasons unattributable to age or gender.

The relevant case in Section 4 is heterogeneity in firm marginal costs, ξ_j, and spatially varying premium tax rates, $t_s p_{js}$. Returning to the first-order condition for prices, we have

$$0 = \sum_{s \in \mathcal{S}} (Q_{js}^h + Q_{js}^\ell)\left[1 - t_s - \left(\frac{(1 - t_s)p_j - \xi_j}{p_j}\right)\Delta_{js}\right] = \sum_{s \in \mathcal{S}} \delta_{js}^{\mathrm{b}}\left[(1 - t_s)p_j - ((1 - t_s)p_j - \xi_j)\Delta_{js}\right]. \tag{B.5.1}$$

where $\Delta_{js} \equiv \delta_{js}^{\mathrm{w}\ell}\varepsilon_\ell + \delta_{js}^{\mathrm{w}h}\varepsilon_h$. Solving for p_j, we now come to

$$p_j = \left(\frac{\sum_{s \in \mathcal{S}} \delta_{js}^{\mathrm{b}}\Delta_{js}}{\sum_{s \in \mathcal{S}} \delta_{js}^{\mathrm{b}}(1 - t_s)(\Delta_{js} - 1)}\right)\xi_j. \tag{B.5.2}$$

When there is no spatial heterogeneity in taxes, this simply reduces to $p_j = (1 - 1/\zeta_j)\xi_j$ as in the benchmark case.

B.6 Endogenizing Local Hiring Costs

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

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

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

$$f_s = \mathbb{E}_s[c_i] + \Gamma_s \left(L_s^n \right)^\varsigma.$$

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

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

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

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

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.

B.8 Incorporating Online Sales

This section outlines a framework that incorporates digital platforms into the market penetration function. Let D_j denote some aggregate quality measure of insurer j's digital platform. D_j could potentially depend on advertising, website design, or integration with their agent force, and is ultimately a choice variable for the insurer. Market penetration now takes the form

$$\kappa_{js}(a_{js}, D_j) = \varsigma \kappa_{js}^{\text{LA}}(a_{js}) + (1 - \varsigma)\kappa_{js}^{\text{DP}}(D_j),$$

where κ_{js}^{LA} is the market penetration of insurer j's *Local Agents*, and κ_{js}^{DP} is the market penetration of insurer j's *Digital Platform*. The parameter $\varsigma \in [0, 1]$ dictates the importance of each distribution system. For example, if $\varsigma = 1$, then only local agents matter; this is the case in the benchmark model. As ς tends to 0, then agents are not important on this margin at all, and everything is done digitally.

The parameters can be calibrated with data on online versus agent-based sales, preferably at the insurer-level, and survey data on household awareness of different distribution methods. The latter is broadly available, but doesn't necessarily translate into sales. According to LIMRA (2022), households are increasingly likely to shop for insurance policies online. However, the strong persistence of agent-based sales suggests that households don't ultimately purchase the policy online, and instead consult with an agent.

C Additional Tables and Figures

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
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: This table reports summary statistics for the NAIC-SBS data across the states in the sample excluding Delaware. Number of insurers refers to all insurance companies in my sample that license at least one local agent in each state. Number of agents refers to the total number of unique local agents. Agent Density is the number of agents per thousand households. Agent-CZ concentration is a measure of how concentrated agents are across commuting zones within each state. Higher values correspond to more spatially concentrated markets. Number of CZ's refers to the total number of commuting zones accounted for in each state.

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: This table reports summary statistics for the Compulife data. All prices are normalized by the respective actuarial value. The data are reported for June of 2018.

TABLE C.3: 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)
Size		−0.049	−0.017
		(0.025)	(0.027)
Leverage		0.025	0.014
		(0.017)	(0.019)
Stock		−0.034	−0.022
		(0.048)	(0.048)
Return on Equity		0.017	0.028
		(0.019)	(0.023)
Agent Competition			0.026
			(0.018)
Agent Market Share			−0.047
			(0.023)
Firm Controls		✓	✓
Competition Controls			✓
Age × Maturity Fixed Effects	✓	✓	✓
Observations	746	746	746
Within R^2	0.32	0.35	0.37

Note: This figure reports the full 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 insurer and reported in parentheses.

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 two regressions:

$$\log p_j^{agm} = \gamma_{g(j)} + \gamma_{agm} + \varepsilon_{jg}$$
$$\log p_j^{agm} = \gamma_j + \gamma_{agm} + \varepsilon_{jg}$$

Here, $\gamma_{g(j)}$ is a group fixed effect, and γ_j is an insurer fixed effect. I consider prices from 2007-2018, and restrict the analysis to insurers in which at least one other group member is present in the data for a given product-year. The first regression recovers the variation in prices conditional on product type (age, maturity, sex) that comes from group-level prices, and the second regression recovers the variation in prices coming at the firm-level. If groups price discriminate through organizational structure, we should expect a large jump in explanatory power in the second regression. I report the within-product R^2 values for each regression.

The group fixed effect explains 57.7% of variation conditional on product-type, while the insurer-level fixed effect explains 63.6%. In percentage terms, the group-level fixed effect alone explains 90.7% of the variation that the insurer-level fixed effect explains. This large share of explanatory power suggests that the majority of the variation in prices is at the group-level.

D.2   Lapsation Sensitivity Analysis

This section reports alternative estimates for the demand estimation with no assumed lapsation in the actuarial values. Table D.4 reports the results. Due to the similarities with the baseline estimates, I omit the demand component estimates.

D.3   Firm Parameter Estimates

This section graphically reports the distribution of demand components, marginal costs, and productivities of insurers for which I have price data. Figure D.1 reports the results.

I plot each measure as a function of insurer size, measured as the log of their total liabilities. Productivities (Panel D.1a) are U-shaped in insurer size: neither small nor large insurers are very productive, requiring many agents to acquire their sales. The middle of the distribution is the most productive.

However, there is a linear relationship between size and demand components (Panel D.1b, with large insurers having the largest demand components. This makes sense intuitively: small insurers

	Variable Annuity Losses			Annuity Prices		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Price	−4.335	−4.526		−1.184	−0.311	
	(0.098)	(0.062)		(0.446)	(0.533)	
Log Price × $\tilde{\chi}_s$	−2.825	−2.165	−1.922	−2.884	−2.543	−2.702
	(0.048)	(0.049)	(0.028)	(0.000)	(0.000)	(0.000)
Demand Controls	✓	✓		✓	✓	
Productivity Proxy		✓			✓	
Firm-Year FE			✓			✓
Agents				✓	✓	✓
Obs	11561	11006	12443	949	949	949
Within R^2	0.15	0.16	-0.02	0.29	0.75	0.09
F	132.0	149.6	494.7	36.4	56.8	115.5

Note: Estimation results for regression equation (14) when assuming no lapsation in policies. 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.

are simply not productive nor attractive, but large insurers may sacrifice investment in their agents' productivity for investment along other dimensions such as advertising or brand value. The medium-sized firms may not be able to invest as much in advertising, and therefore target agent training as a way to build sales, making them more productive than the largest insurers.

Finally, marginal costs are weakly downward sloping in insurer size. This likely reflects a different form of productivity based on processing costs and underwriting, where large insurers have an advantage.

D.4 INCORPORATING RACIAL DEMOGRAPHICS IN DEMAND ESTIMATION

This table reports demand estimation results when I further disaggregate states into high- or low-minority population share groups. I first calculate the median per-capita income and the median non-white share across states. I then assign states to one of four groups based on whether they are above or below each of those thresholds. The groups are close to balanced: of states below median income, 14 are below median non-white share and 11 are above median non-white share; of states

(a) Productivity   (b) Demand Components   (c) Marginal Costs
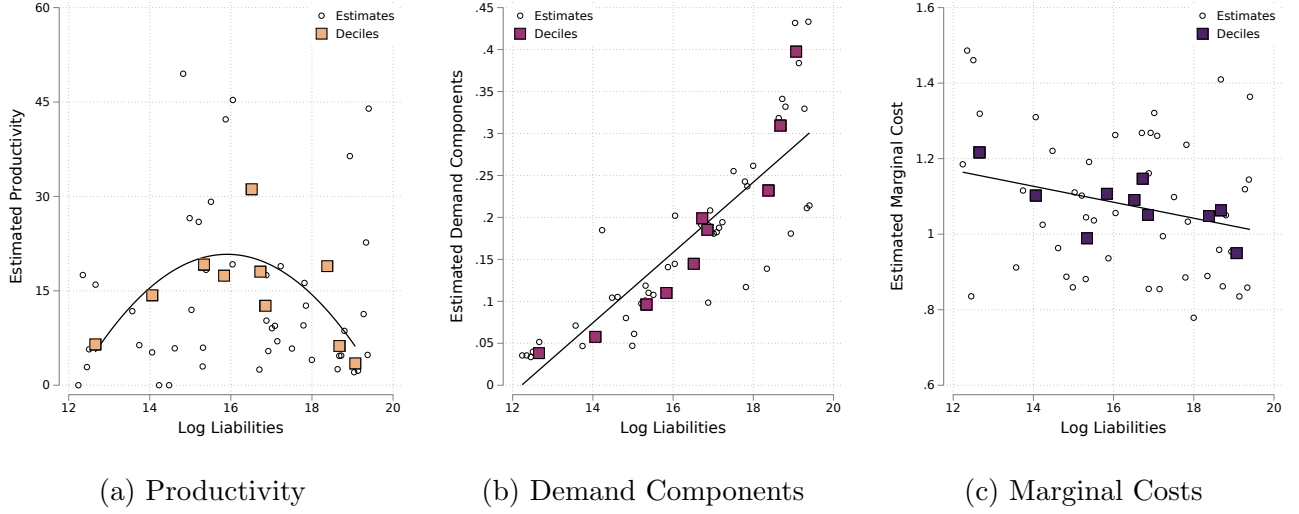
Note: This figure documents percentage changes in welfare induced by national pricing against commuting zone high-income population share. All lines are local polynomials estimated with the Epanechnikov kernel. Dark areas represent high-income household changes and transparent areas represent low-income 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.

above median income, 11 are below median non-white share and 13 are above median non-white share.

I take the base group to be low-income states that are below median non-white share. The regression specification is then

$$\log S_{js} = \log a_{js} + \log \theta_j + \log \omega(\boldsymbol{X}_j^f) - (\varepsilon_\ell^w - 1)\log p_j + \sum_k (\varepsilon_\ell^w - \varepsilon_k)\chi_s^k \log p_j + \text{FE}_s \qquad \text{(D.4.1)}$$

where the summation over k refers to the remaining three groups. Table D.4.1 reports the results of the regression for the six specifications in the main text. I omit estimates of the demand controls since they change very little from the estimates in the main text.

D.5 MODEL FIT

This section reports the overall fit of the model. First, I simply regress the number of agent-insurer pairs in the data against the number of agent-insurer pairs in the model. The R^2 of this regression is 0.61, and the correlation coefficient between the model and the data is 84%. Figure D.2a plots the model against the data. The figure suggests that the model overestimates the number of agents in smaller locations. This is confirmed in Figure D.2b, which plots the difference in agents between model and data against log population and recovers a negative slope.

TABLE D.5: DEMAND ESTIMATION RESULTS WITH RACIAL CATEGORIES

	Variable Annuity Losses			Annuity Prices		
	(1)	(2)	(3)	(4)	(5)	(6)
Low Inc × White	−2.903	−3.172		−2.687	−1.783	
	(0.226)	(0.139)		(0.086)	(0.000)	
High Inc × White	−4.362	−2.038	−3.175	−1.487	−1.374	−1.489
	(0.026)	(0.017)	(0.004)	(0.001)	(0.000)	(0.000)
Low Inc × Non-White	−3.251	−3.069	−2.207	2.551	2.505	2.532
	(0.049)	(0.037)	(0.012)	(0.000)	(0.000)	(0.000)
High Inc × Non-White	−4.163	−3.267	−2.652	−1.168	−0.607	−0.786
	(0.032)	(0.021)	(0.012)	(0.137)	(0.367)	(0.261)
Demand Controls	✓	✓		✓	✓	
Productivity Proxy		✓			✓	
Firm-Year FE			✓			✓
Agents				✓	✓	✓
Obs	11561	11006	12443	949	949	949
Within R^2	0.13	0.15	-0.06	0.29	0.75	0.09
F	65.8	74.4	164.3	18.0	26.1	35.2

Note: Estimation results for regression equation (D.4.1). 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.

Next, I perform an over-ID check of the estimated model. The estimation uses data on N_s and η_s^h taken from the 2016-2020 wave of the ACS. I solve the model again using data instead from the 2006-2010 wave and use the model to predict the number of agents in each commuting zone with these fundamentals.

I compare the estimates of the model to the changes in agents across commuting zones in the data. I use the NAIC-SBS data to infer agents in 2010 using initial licensing dates of each agent-insurer pair. A caveat of this exercise is that the agent data is inaccurate for 2010 since the data do not include the agents that exited between 2010 and 2022. I supplement the agent data with data on broker and financial intermediary employment taken from the Quarterly Census of Employment and Wages. The results are very similar, so I only report results from the baseline.

(a) CZ-level Model Fit

(b) Fit Against CZ Population
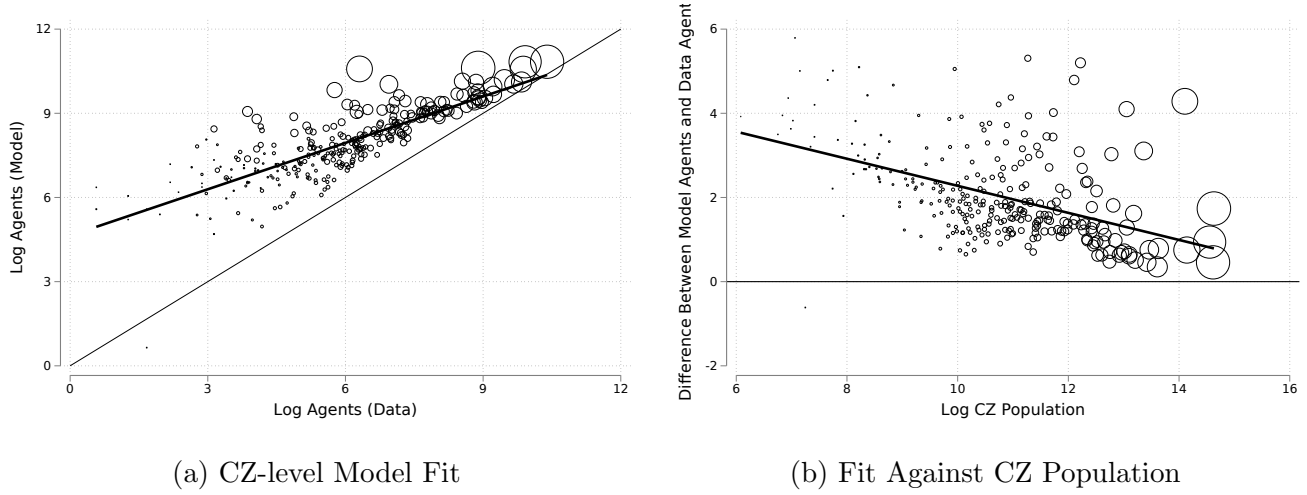
Note: This figure documents the fit of the model at the commuting zone level. Panel (a) plots the log number of agents in each commuting zone in the model against the log number of agents in the data. Panel (b) plots the difference between model and data against log commuting zone population.

Figure D.3 displays the fit of the model in three ways. First, Panel D.3a plots the change in agents in the model and data against the change in commuting zone high-income share. The model underestimates the large gains in the stable locations, but is similar to estimates for commuting zones that became significantly richer. Second, Panel D.3b plots the changes in agents against change in commuting zone population. The model does much better on this dimension. Finally, Panel D.3c plots the change in agents across commuting zone in the model against the data. The R^2 of the regression line is 0.61, implying that the model explains 61% of the variation in the data. This is likely an underestimate due to the measurement error in the early agent data.

FIGURE D.3: RESULTS OF THE OVER-ID TEST

(a) Relative to Flexible Pricing   (b) Relative to Santa Cruz   (c) Relative to Santa Cruz
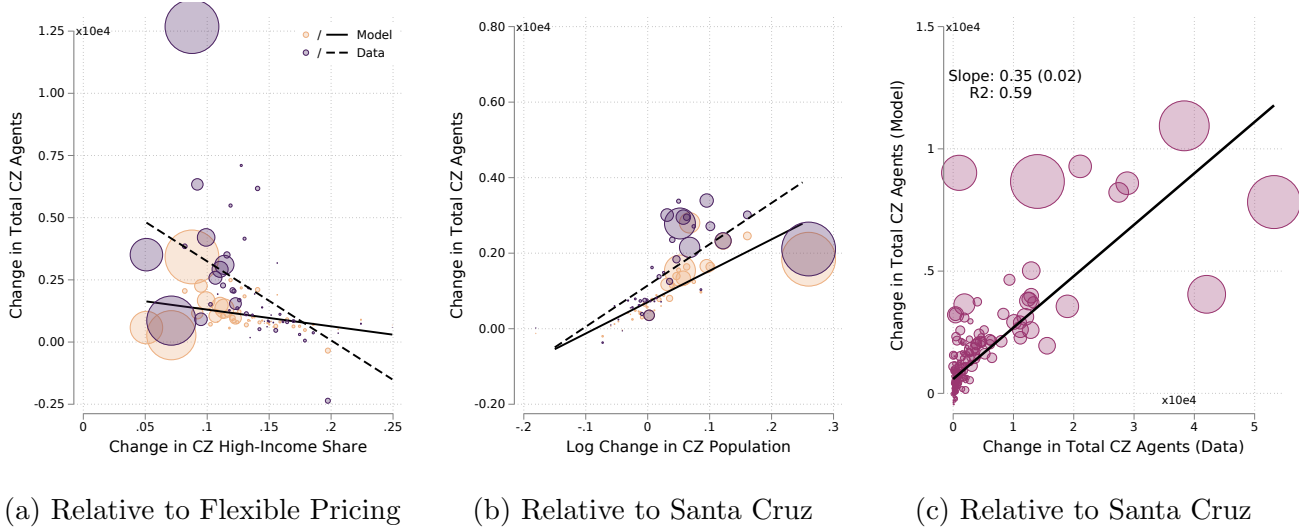
Note: This figure plots changes in agents across commuting zone in the model and the data. Panel (a) reports the changes in agents against the change in high-income population share, and Panel (b) reports the changes in agents against the log change in commuting zone population. Panel (c) plots the model against the data. Panels (a) and (b) plot both the data (purple/dashed line) and the model (tan/solid line) separately.

E ADDITIONAL COUNTERFACTUAL EXERCISES

E.1 DISTRIBUTIONAL EFFECTS WITHIN COMMUTING ZONES

The analysis in Section 5 focuses on the effects of policy on spatial inequality. But this may mask the effects on households relative to the flexible pricing benchmark. For example, it may be that national pricing makes low-income households better off in a commuting zone, but less so than the optimal commuting zone. This section focuses on these within-commuting-zone effects.

I analyze the effects of both the national pricing and place-based tax policies again using compensating differentials. Here, I compute the necessary change in savings for the average household of a given type that equates their welfare to that under flexible pricing.

Figure E.1.1 reports the effects of national pricing decomposed into pricing and access margins. The figure shows that the increase in inequality for low-income households is driven by a decline in welfare for all but the richest decile of commuting zones, driven by the reallocation of insurers' agents. Similarly, the decline in spatial inequality for high-income households is driven by the increase in welfare for high-income households in the majority of commuting zones.

The magnitudes of the welfare effects are small even ignoring the adverse access margin responses. At best, national pricing is equivalent to giving low-income households an additional $3.60 and high-income households an additional $20.40 on the pricing margin. In percentage terms, this is equivalent to an increase in yearly income of 0.01% and 0.02%, respectively. This is due to the

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FIGURE E.1.1: COMPENSATING DIFFERENTIALS WITHIN COMMUTING ZONES
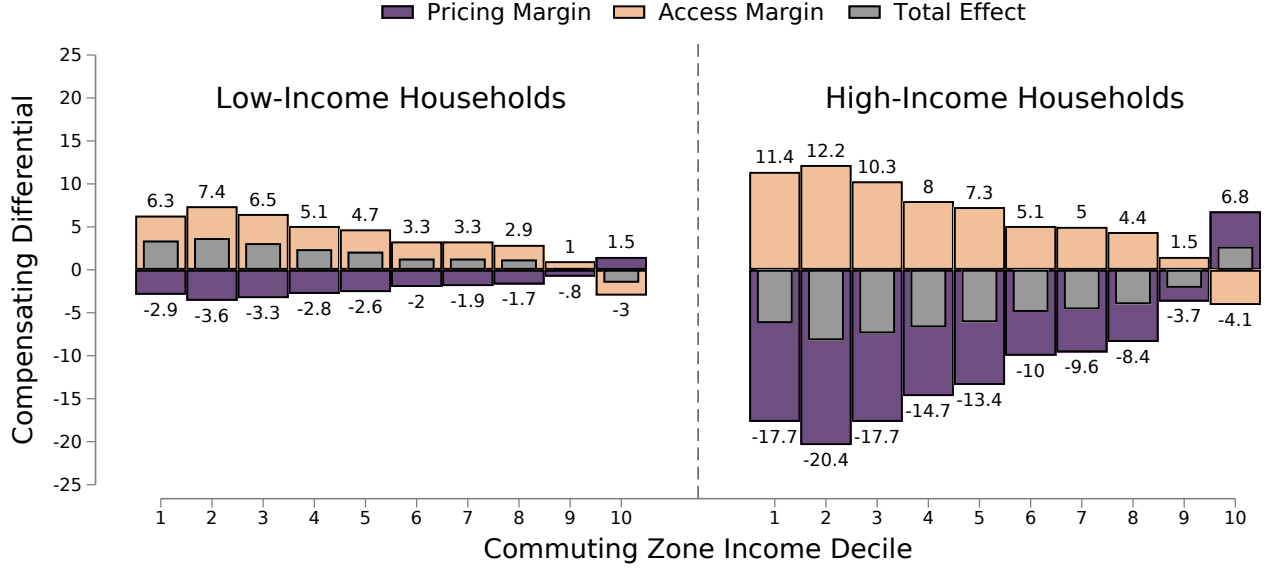
Note: This figure reports compensating differentials across commuting zone high-income population share deciles using commuting zone welfare under flexible pricing as the benchmark. Dark purple bars reflect the pricing margin, while the light tan bars reflect the access margin. I condition on low-income households in the left section and high-income households in the right section.

fact that even in relatively poor locations, sales shares between household types lean toward high-income households, so prices are relatively low even under flexible pricing. National pricing reduces prices slightly, but not enough to induce large welfare changes.

Figure E.1.2 reports the total effects of also incorporating the place-based policies. As the figure shows, the magnitudes of the place-based policy effects are substantially larger than that of national pricing alone.

E.2   WELFARE USING ELASTICITIES FROM THE VA LOSSES INSTRUMENT

For this section, I estimate the model using the elasticities from the variable annuity losses instrument, $\{\varepsilon_k^{\text{VA}}\}$, reported in Column (1) of Table 3. I do not use the alternative demand estimates, however, as the estimated variance in total demand components $\{\omega_j\}$ is substantially larger than in the baseline estimates implied by Column (3). This comes with convergence problems for the SMM routine. Nevertheless, the results provide useful implications about which features of the results are robust to elasticity estimates and which are not.

I first consider how compensated differentials change in the flexible pricing regime between both sets of elasticities. Figure E.2.3 shows the results broken down by margin. Generally, compensating differentials are smaller with higher elasticities. However, the effects of the pricing and access margins have similar proportions the baseline estimates. For low-income households, the access

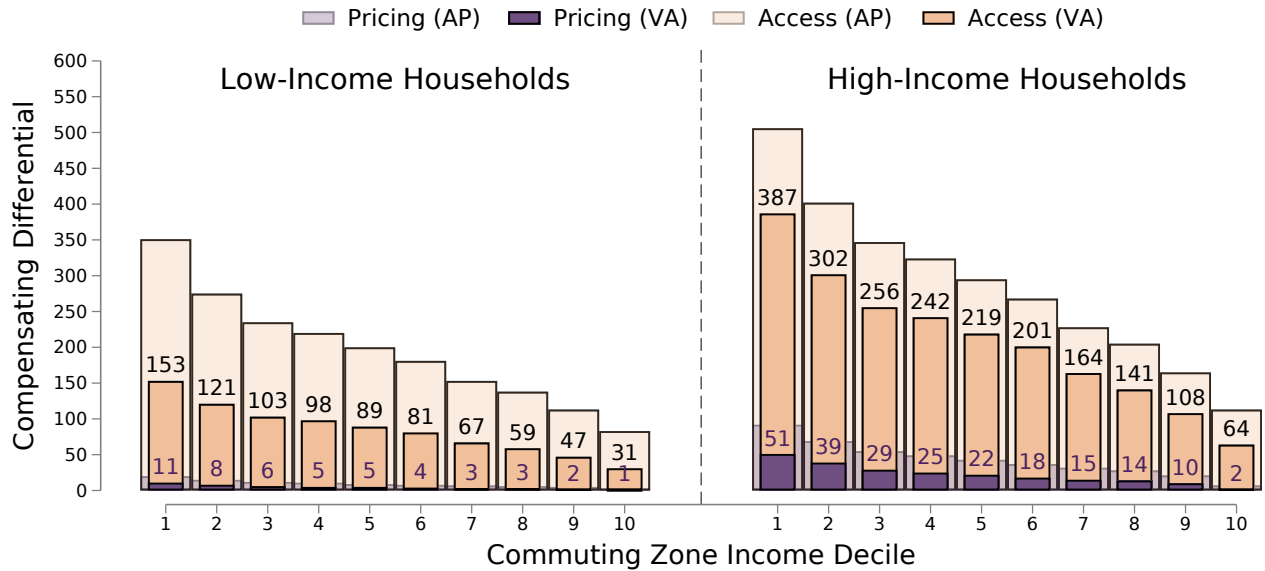FIGURE E.1.2: COMPENSATING DIFFERENTIALS WITHIN COMMUTING ZONES
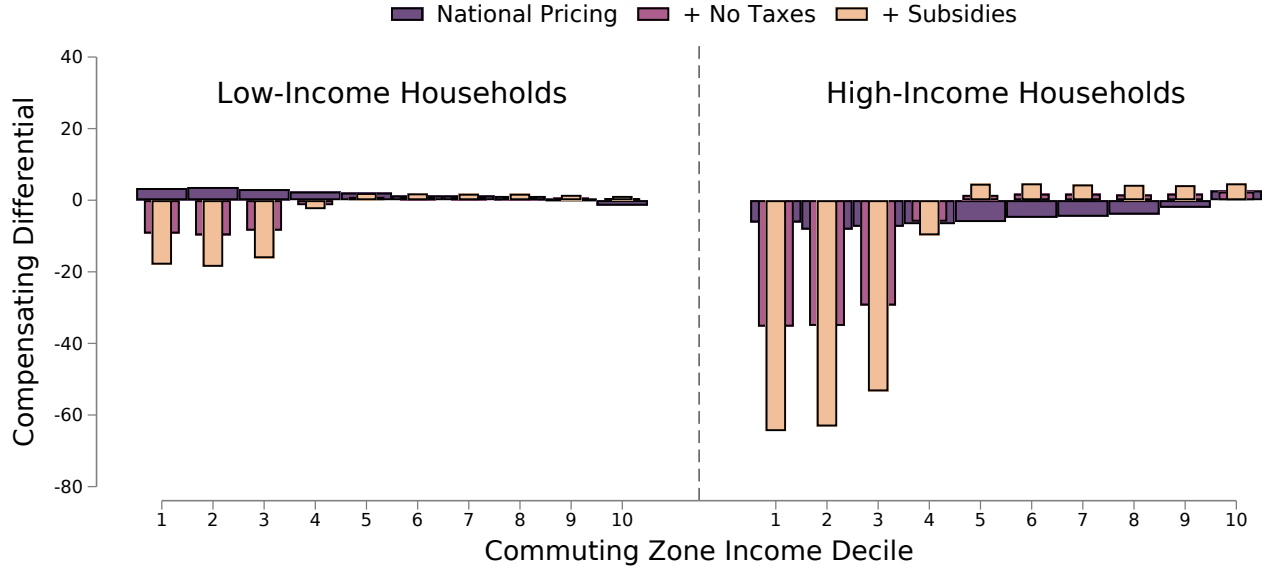
Note: This figure reports the change in compensating differentials across commuting zone high-income population share deciles using commuting zone welfare under flexible pricing as the benchmark. Dark purple bars reflect the effects of national pricing, pink bars reflect the effects of the no-tax policy, and the light tan bars reflect the effects of the subsidy policy. I condition on low-income households in the left section and high-income households in the right section.

margin accounts for 92% of the total differential in the poorest decile, which is similar to the baseline (94%). The differences for high-income households are also similar.

Figure E.2.4 plots the relative effects of national pricing across specifications. Again, the effects are smaller in magnitude, but the relative effects across household types keep the same sign. In particular, low-income households are generally worse off relative to the optimal location, while high-income households are generally better off.

Finally, Figure E.2.5 shows the proportional effects of the subsidy policy under both specifications. In fact, relative to national pricing alone, the effects using the variable annuity losses instrument have a larger percentage increase than the annuity price instrument.

FIGURE E.2.3: WELFARE DISPERSION UNDER FLEXIBLE PRICING
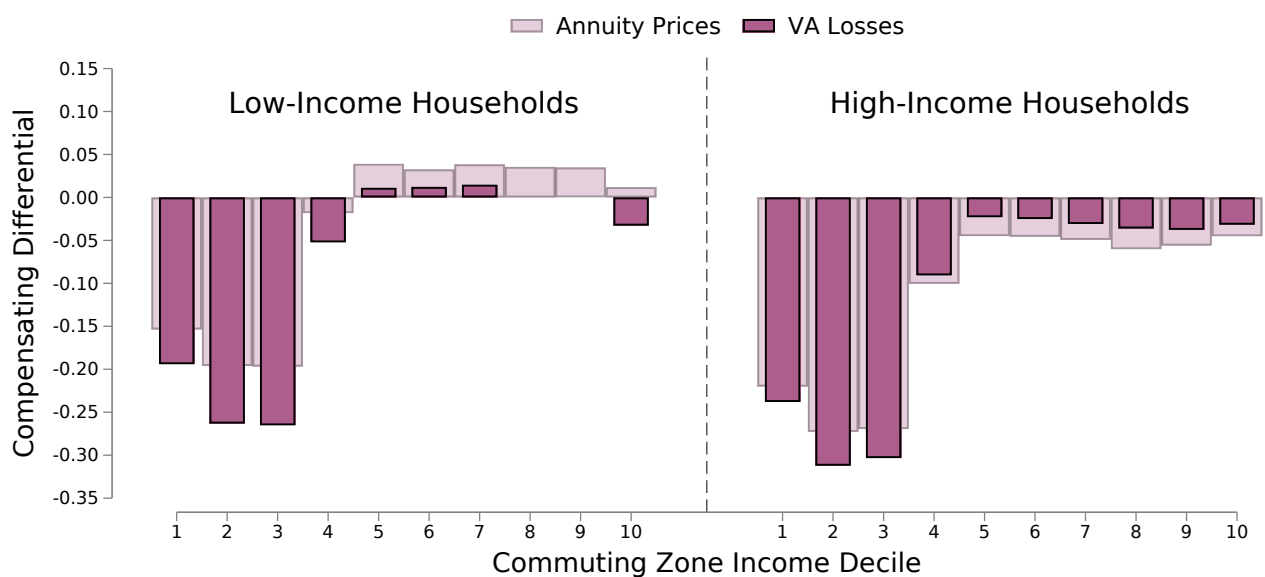

Note: This figure documents compensating differentials across commuting zone income deciles for low- and high-income households for both sets of elasticity estimates. Faded bars represent the estimates under the annuity price instrument (AP) and solid bars represent the estimates under the variable annuity loss instrument (VA).

FIGURE E.2.4: WELFARE DISPERSION UNDER FLEXIBLE PRICING
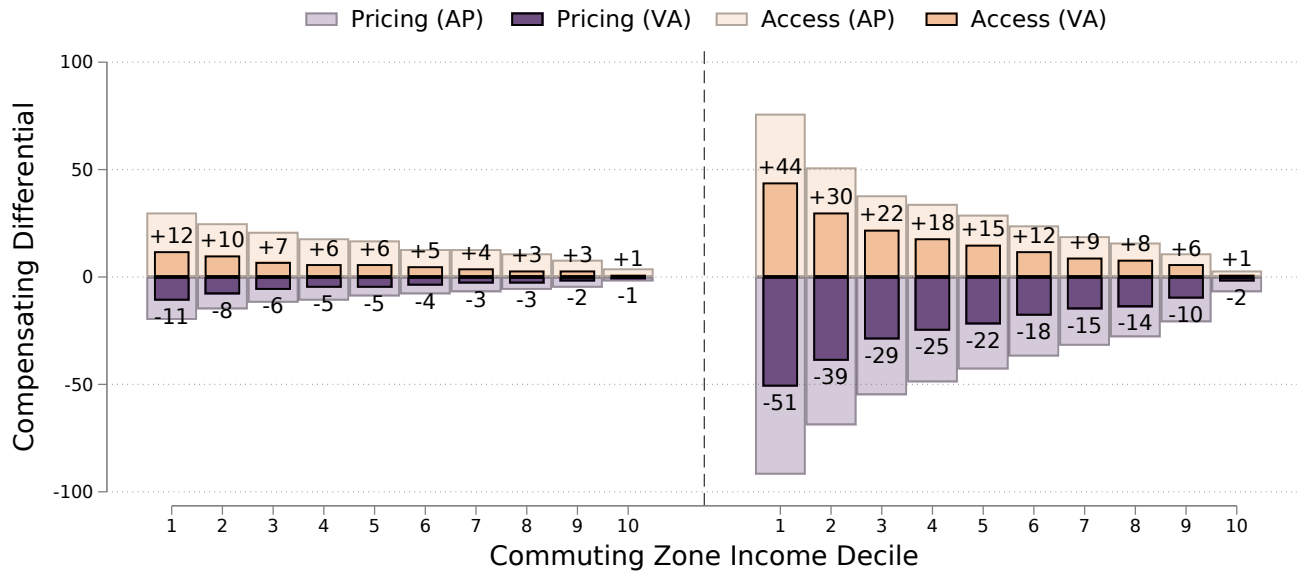
Note: This figure documents the change in compensating differentials under national pricing relative to flexible pricing for both sets of elasticity estimates. Faded bars represent the estimates under the annuity price instrument (AP) and solid bars represent the estimates under the variable annuity loss instrument (VA).

FIGURE E.2.5: WELFARE DISPERSION UNDER FLEXIBLE PRICING

Note: This figure documents the percentage change in compensating differentials under the subsidy policy relative to national pricing for both sets of elasticity estimates. Faded bars represent the estimates under the annuity price instrument (AP) and solid bars represent the estimates under the variable annuity loss instrument (VA).