School Funding, Teacher's Labor Market, and Student Outcomes

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This paper examines the role of school funding mechanisms on determining teacher employment and compensation, and student achievement using a structural equilibrium model. We analyze how variations in school funding policies in Texas affect teacher wages, labor supply, and educational outcomes. We find that the recapture policy-a policy that transfers excess property tax revenue from rich to poor school districts- is crucial in balancing educational resources, influencing both the quantity and quality of teachers, and impacting student achievement. Counterfactual simulations reveal that eliminating the recapture policy allows wealthier districts to offer higher wages and attract more teachers but may lower average teacher quality due to an influx of less-skilled individuals. Less affluent districts face budget reductions and reduced teaching resources but could experience an increase in average teaching quality. Our findings highlight important trade-offs in policy design regarding funding redistribution and educational equity.

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1. Introduction

The quality of education is a cornerstone of societal development, influencing economic growth, health outcomes, and social well-being. Teachers play a central role in this process, as their effectiveness directly impacts student achievement and long-term societal benefits Rivkin, Hanushek, and Kain (2005); Chetty, Friedman, and Rockoff (2014). Despite their importance, teacher labor markets exhibit unique characteristics that differentiate it from other sectors.

In the context of public education systems, school funding mechanisms are an important factor for teacher compensation and labor market dynamics. Funding systems that rely heavily on local property taxes can create disparities in resources among districts, affecting schools' ability to offer competitive salaries and attract qualified teachers. In Texas, a "recapture" policy has been in effect since 1994, where districts with local property taxes above certain thresholds transfer resources to poorer districts. While the original motivation was to create a more equitable distribution of resources, critics argue that the larger districts are being unjustly penalized.

Motivated by these complexities, this paper develops and estimates a model to examine the interplay between school funding, teacher wages, labor market dynamics, and student academic achievement within Texas ISDs. Different levels of revenue generates varying wage levels across ISDs. This in turn influences employment choices of potential teachers, especially when comparing wage offers in non-teaching jobs in each ISD. With a change in who chooses to be employed in the teaching sector, student achievement will also be impacted due to different composition of teaching skills.

We incorporate these aspects into a structural model of potential teachers, school districts, and student achievement to analyze the impact of counterfactual changes to the recapture policy in Texas. In our framework, workers decide whether to become teachers, work in the non-educational sector, or engage in home production, considering both pecuniary and non-pecuniary factors. We model this choice using a Roy model, which allows us to separately estimate individual teaching skills and skill prices. On the other side, school districts determine teacher wages by maximizing student achievement under a teacher value-added framework. Districts are subject to budget constraints influenced by school funding policies, particularly the recapture policy.

We integrate the Texas school funding system into our model, focusing on the educational sector's budget constraint and the recapture policy. Our model simulates how variations in school funding, driven by these policies, affect teacher wages and the distribution of workers across districts. By linking the labor supply decisions of potential

teachers with the budget constraints and objectives of schools, our model captures the general equilibrium effects of school funding policies on the teacher labor market and student outcomes.

We estimate our model using detailed data from Texas, including teacher salaries, school funding information, and student achievement measures. We estimate both the labor supply and the school district problems using the Method of Simulated Moments. The results show that the recapture policy plays a critical role in balancing educational resources across districts, influencing both the quantity and quality of teachers, and ultimately affecting student achievement.

We then conduct counterfactual experiments to assess the impact of policy changes, specifically the elimination of the recapture policy. This analysis quantifies the relative importance of demand and supply-side factors in determining teacher policy effectiveness. The counterfactual simulations reveal that removing the recapture policy leads to significant shifts in the distribution of teacher skills and student achievement across districts. Wealthier districts can offer higher wages, attracting more teachers but potentially lowering average teacher quality due to an influx of less-skilled individuals. Conversely, less affluent districts may experience budget reductions due to the elimination of recapture payments, leading to a decrease in the number of teachers they can hire. However, as the less skilled teachers are more likely to leave, the average teaching quality in these districts may increase despite the overall reduction in total teaching resources.

This paper is closely related to Tincani (2021) and Biasi, Fu, and Stromme (2021). First, it extends the structural models of teacher labor markets by providing a general equilibrium framework that captures the interaction between individual occupational choices and school wage-setting behavior, Unlike these studies, which focus on specific policy reforms in Chile and Wisconsin respectively, our paper examines the impact of a school funding equalization policy in Texas, offering insights into how such policies affect teacher labor markets and educational outcomes in a different institutional context. Second, our model explicitly incorporates the recapture policy's role in redistributing funds and its effects on both teacher supply and student achievement, a feature not previously explored in the literature. Third, we provide empirical evidence on the trade-offs between the quantity and quality of teachers resulting from changes in school funding, highlighting the importance of considering both aspects in policy design.

This paper contributes to a growing literature analyzing the effects of school funding policies on teacher labor markets and student outcomes. Lafortune, Rothstein, and Schanzenbach (2018) studies school finance equalization (SFE) reforms, documenting how these policies reduce resource disparities and improve educational outcomes in low-

income districts. Using data from states with SFE reforms, the study finds that revenue growth in these districts increased more than double the rate observed in non-SFE states, leading to substantial gains in student achievement. In this respect, Lafortune, Rothstein, and Schanzenbach (2018) complements this paper, as both highlight the importance of targeted resource allocation in achieving educational equity. While their focus is primarily on funding levels, our approach examines how these financial changes propagate through the teacher labor market, shaping wages and educational outcomes.

Biasi (2023) builds on this line of work by investigating the causal effects of school funding equalization on intergenerational income mobility (IGM). Using a simulated-instruments approach to address endogeneity, the study demonstrates that equalizing revenues significantly boosts IGM, particularly in states with high inter-district competition and income inequality. This paper draws on similar insights, emphasizing that funding reforms influence not just student achievement but also broader socio-economic outcomes, mediated by changes in teacher compensation and distribution.

Another related stream of literature focuses on the structural modeling of teacher labor markets. Tincani (2021) uses a structural model to evaluate the effects of merit-based teacher reforms in Chile. They simulate the impact of these reforms on teacher welfare and labor market dynamics, incorporating decisions of schools and teachers across public and private sectors. Unlike this paper, Tincani (2021) emphasizes the role of private sector competition, whereas we focus on the dynamics within public school systems. Biasi, Fu, and Stromme (2021) also employs a structural model to examine the effects of Wisconsin's flexible salary law on teacher sorting and district hiring strategies. Their work complements ours by exploring how wage flexibility alters teacher allocation across districts, while we analyze how funding disparities affect teacher compensation and student outcomes in a more constrained wage-setting environment.

Finally, this paper relates to studies exploring the broader impacts of school funding on long-term educational outcomes. Card and Payne (2002) and Jackson, Johnson, and Persico (2016) find that increased school spending improves educational attainment and earnings, especially for disadvantaged students. However, few studies investigate the intermediate channels through which funding achieves these outcomes. This paper contributes to this literature by modeling teacher labor market dynamics as a key mechanism linking funding changes to student achievement. Our structural approach allows us to evaluate the ex-ante impacts of SFE policies on both teacher composition and educational outcomes, offering a more comprehensive understanding of the funding-to-outcome pathway.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on school finance equalization, teacher labor markets, and educational out-

comes. Section 3 provides background information on Texas's school funding system and describes our data sources. Section 4 presents descriptive results highlighting key patterns in funding, teacher wages, and student achievement across districts. In Section 5, we introduce our structural model and discuss the estimation strategy. Section 6 shows our estimation method. Section 7 presents the results of our analysis, including the counterfactual simulations of policy changes. Section 8 concludes.

2. Texas School Funding Background and Data Description

2.1. Texas School Funding

Texas has 1,204 school districts and charter schools, the Independent School Districts (ISDs) employs 705,000 people (over half are teachers), and educates 5.4 million students. Funding for 2020-21 totaled $70.4 billion, which included $27.2 billion (39%) in state funds, $37.8 billion (53%) in local property taxes, and $5.4 billion (8%) in federal funds Texas Education Agency (TEA). The Foundation School Program (FSP) is the state program administered by the Texas Education Agency (TEA) that establishes the amount of state and local funding due to ISDs. Its primary goal is to ensure that school districts receive "substantially equal access to similar revenue per student at similar tax effort, considering all state and local tax revenues of districts after acknowledging all legitimate student and district cost differences."

The FSP assists school districts in financing maintenance and operations through two formulas: Tier One (basic funding), responsible for funding the main operations of a school district (e.g, basic education, compensatory education, bilingual education, teacher incentives, transportation, etc.); and Tier Two (supplementary funding, also referred as enrichment), which guarantees a specific level of funding per student given a weighted average daily attendance (WADA) for each penny of tax effort above a school district's maximum Tier One tax rate.

The basis of Tier One funding comes from the basic allotment (BA) per student, which for 2020-21 biennium was $6,160. The BA amount and the number of students in average daily attendance (ADA) are used to calculate districts' Tier One entitlement. Furthermore, each school district has its own Cost of Education Index (CEI), which is a multiplier to compensate the district for geographic and cost differences beyond the control of the district. Components used in the calculation of the CEI are the average beginning salary of teachers in contiguous districts, the number of economically disadvantaged students in the district, the district's size, and whether or not the district is located in a rural county.

The state and school districts are responsible for funding the Tier One entitlement. Local fund assignment, also known as local share, is the portion due to the school district and it comes from local property taxes. The total Tier One entitlement minus the local share equals the state's share of the Tier One. If the school district's share is greater than the calculated Tier One total entitlement, the district is said to be "budget balanced". The revenue in excess is then transferred to the state to finance other districts' shortages. This transfer policy is known as "recapture," or the "Robin Hood" policy, referring to the practice of reallocating funds from wealthier districts to less advantaged ones

The TEA determines the amount of recapture owed by a district by calculating the percentage of the district's taxable value above a threshold level and then applying that percentage to the current year's maintenance and operations taxes collected by the district. In the 2017-18 school year, year analyzed in this paper, 191 school districts were required to make recapture payments. The percentages of local property taxes recaptured range from a low of 1% (many districts) to a high of 92% (Westhoff ISD). This system was enacted in 1993; in 1994, $131 million was recaptured from 104 districts. Approximately $2.1 billion was recaptured from a total of 191 school districts in the 2017-18 school year Texas Education Agency (TEA). These school districts encompass 19% of all districts and contain 1.2 million weighted students or 19% of the statewide total. Austin ISD sends away approximately $516 million after credits (48% of its M&O taxes), more than any other district in gross dollars.

2.2. Data Wrap Up - Datasets Used, Target Population, Measures

In this section, we briefly describe the datasets used in our analysis, the target population, and the measures employed to operationalize the model variables. The main datasets are the American Community Survey (ACS-PUMS), the Education Research Center (ERC), and the Public Education Information Management System (PEIMS) Financial Data. We also discuss the criteria used to define the target population of workers and students.

2.2.1. Datasets

- **ACS-PUMS**: The American Community Survey's Public Use Microdata Sample (ACS-PUMS) provides detailed demographic and labor market information. We extract key demographic characteristics such as gender, age, race, ethnicity, employment status, and income. This dataset is essential for understanding individual-level labor market outcomes and occupational choices in Texas.
- **ERC**: The Education Research Center (ERC) provides longitudinal, student-level data for Texas public school students. It includes academic records, demographic informa-

tion, and standardized test scores from the Texas Education Agency (TEA) and higher education records from the Texas Higher Education Coordinating Board (THECB). ERC also provides data on labor market outcomes through the Texas Workforce Commission (TWC), including Unemployment Insurance (UI) records.

- **PEIMS Financial Data**: The Public Education Information Management System (PEIMS) provides financial data from Texas Independent School Districts (ISDs). We use data on district-level revenues, expenditures, payroll, recapture, and student enrollments. PEIMS financial data helps quantify school district resources and allows us to compute values on a per-student basis.

2.2.2. Target Population

Our study focuses on individuals in Texas during 2017, covering both students and workers. For students, we gather data primarily from high school years. In terms of workers, we focus on individuals employed in both the education and non-education sectors, analyzing their occupational choices and wages in the year 2017.

2.2.3. Measures

In this subsection, we define how we measure each variable that we use in our analyses.

- **Demographics**: We use demographic data both from the ACS-PUMS and ERC datasets, including information on gender, race, ethnicity, English as a Second Language (ESL) status, and eligibility for free or reduced-price lunch. These variables provide a baseline for controlling individual characteristics in both the labor supply and achievement models.
- **Employment and Home Production**: We define employment status using a the ACS-PUMS data. We categorize individuals as employed, engaged in home production (if working fewer than 27 weeks per year and less than 20 hours per week). If individuals hold multiple jobs, we consider the job with the highest labor income. This classification is important for identifying the occupational choices and economic activities of the target population.
- **Achievement**: We use standardized Algebra 1 and English I test scores from the State of Texas Assessments of Academic Readiness (STAAR) as our measure of academic achievement. STAAR exams are designed to evaluate student mastery of key academic standards and provide a consistent framework for assessing performance across schools.

Focusing on Algebra and English allows us to analyze critical skills that are foundational for student success in both academic and professional contexts, ensuring the reliability and comparability of our results.

- **Financial Data**: Financial data from PEIMS provides detailed information on school district revenues, expenditures, and student enrollment figures. We calculate financial metrics such as operational revenue per student, payroll per student, and total expenditures per student to evaluate the financial resources available to different districts and their impact on student outcomes.

A detailed breakdown of the model variables, including how they were computed, is provided in Appendix A.

3. Descriptive Results

3.1. PEIMS - Financial Data

The Public Education Information Management System (PEIMS) is a comprehensive database managed by the Texas Education Agency (TEA), encompassing a wide array of data related to public education in Texas. Established in the 1980s, PEIMS is one of the largest educational databases in the world, providing information on financials figures, and organizational structures of over 1,200 districts and charter schools. This section focuses on publicly available audited financial records of each Texas Independent School District (ISD). After cleaning the data, our analysis is confined to 1,014 ISDs that have been mapped for this study. Within this subset, 168 ISDs are subject to the state's recapture policy, which redistributes excess local property tax revenue to less affluent districts.

Since our model is a static one, we've chosen a pre-pandemic year (2017) for our analysis. The financial data from the PEIMS provides information on various aspects of school district finances, including revenues by source, expenditures by function, amounts recaptured, and the number of students enrolled. Table 1 offers a comparative analysis of financial metrics between recapture and non-recaptured ISDs. Significant differences are evident in operational revenue and expenditure, payroll and materials expenditures per student. Recaptured funds constitute roughly 46% of the local revenue in recaptured ISDs, with these districts reporting an average local tax revenue of 10,145 per student, net of recapture transfers, compared to 4,281 in non-recapture ISDs.

In our analysis, we utilize regional Education Service Centers (ESCs) as our primary market unit, these Centers function as service organizations of the TEA. There are twenty

ESCs, their main purposes include assisting school districts in improving student performance, helping districts operate more efficiently, and implementing initiatives assigned by the legislature or the commissioner. The map below in Figure 1 highlights each ESC region and shows in white border which ISDs are subject to the recapture policy.

The decision of using ESCs as our market unit aligns the PEIMS dataset with the Public Use Microdata Sample (PUMS) dataset, allowing for a more coherent analysis. While ISD-specific wage data is not available, we do have wage data by Public Use Microdata Areas (PUMAs). Unfortunately, there is no direct correspondence table linking each PUMA to an ISD. However, we can bridge this gap using a combination of PUMA-Census Tract and Census Tract-Local Education Agency Identification System correspondences.

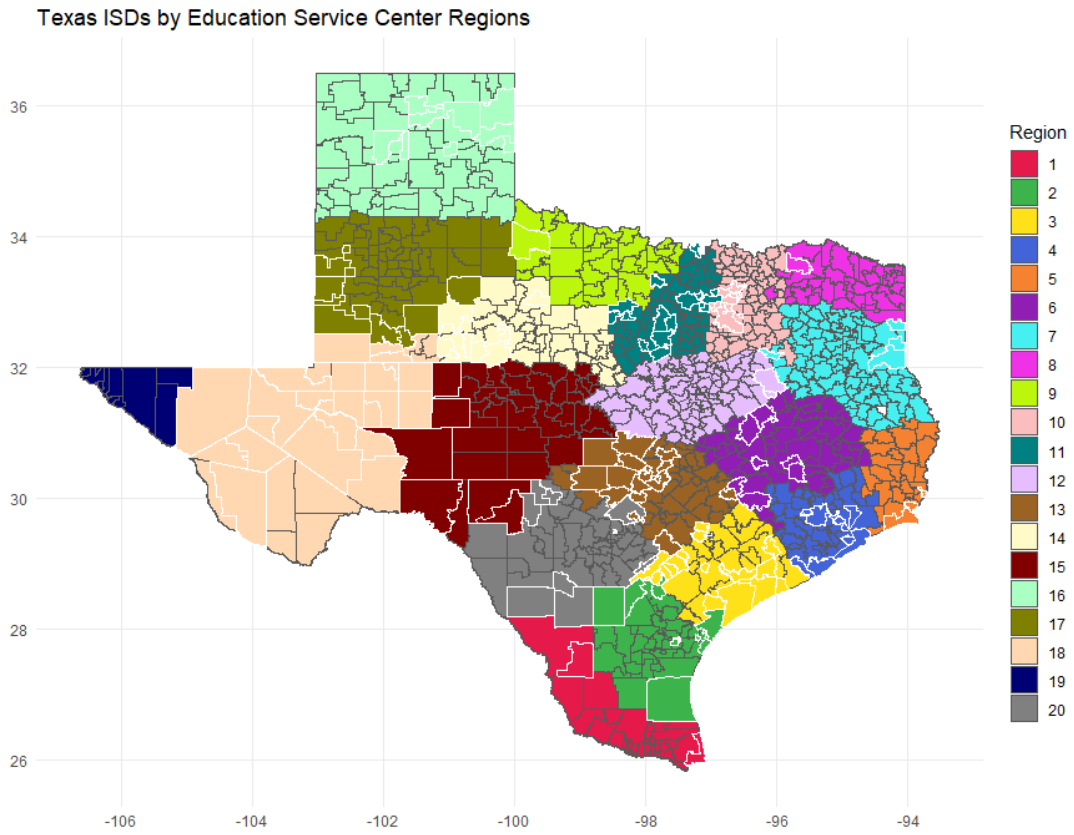
TABLE 1. Financial Figures Across ISDs Subject to and Not Subject to the Recapture Policy

Variable	Non-Recapture ISDs	Recapture ISDs	Differences
Number of Districts	846	168	-
Average of Students	4,970.67	5,205.04	-234.36
Recaptured p/ Student ($)	0	8,504.72	-8,504.72***
Local Tax Rev. p/ Student ($) Net of Recapture	4,281.53	10,145.03	-5,863.50***
Operational Rev. p/ Student ($) Net of Recapture	12,368.31	14,619.47	-2,251.16***
Operational Exp. p/ Student ($)	11,760.77	13,332.51	-1,571.74***
Payroll p/ Student ($)	8,794.58	9,754.48	-959.90***
Services p/ Student ($)	1,343.91	1,846.83	-502.92**
Materials p/ Student ($)	1,118.52	1,208.79	-90.28*

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows summary statistics for the financial data. The data comes from the Public Education Information Management System (PEIMS) public financial data from 2017. The values exhibit the average per student expenditures and revenues of Independent School Districts (ISDs) depending on whether the ISD is subject to recapture or not.

A PUMA is a geographic unit with a minimum population of 100,000 people, whereas Census Tracts typically contain up to 8,000 people. By utilizing the Census Tract-Local Education Agency Identification System correspondence, we can assign each Census Tract to a specific Region. Similarly, with the PUMA-Census Tract correspondence, we can map each Census Tract to its respective PUMA. This methodology allows us to establish a PUMA-Region correspondence. In cases where a single PUMA spans multiple Regions, we determine the predominant Region for that PUMA by counting the number of Census Tracts within the PUMA that belong to each Region. The Region containing the majority of the Census Tracts for a given PUMA is then designated as the containing Region for that PUMA.

FIGURE 1. Map of Education Service Centers Regions.



Note: The 20 ESC Regions. ISDs subject to recapture are outlined with white borders.

Table 2 below presents a breakdown of financial data across the twenty Education Service Centers (ESCs) in Texas. Each region varies significantly in terms of the number of districts and the percentage of districts subject to recapture. For instance, Region 19 has only 12 districts, none of which are subject to the recapture policy. In contrast, Region 18 has 33 districts, with a substantial 48% of them subject to recapture. The values presented in the table are calculated by summing the relevant financial figures across all districts within each region and then dividing by the total number of students in that region. This method ensures that the data reflects a per-student basis for the region as a whole, which can differ from individual district-level means shown in Table 1. Despite the relative consistency in operational expenditures and revenue across regions, the significant variability in local tax revenue and recaptured values will be highly valuable for our model and estimation.

Table 3 presents the financial differences between recaptured and non-recaptured districts within each ESC region. The differences are calculated as the mean values for recaptured districts minus the mean values for non-recaptured districts for each variable. As expected, recaptured districts exhibit significantly higher local tax revenue per student

TABLE 2. Summary Statistics of Financial Figures Across Regions

Region	Number of Districts	% Subject to Recapture	Recaptured p/ Student ($)	Local Tax Rev. p/ Student ($) - Net of Recapture	Operations Rev. p/ Student ($) - Net of Recapture	Operations Exp. p/ Student ($)
1	36	0.08	48	2,111	11,598	11,430
2	42	0.21	779	4,819	11,447	10,857
3	38	0.39	1,386	5,900	11,994	11,034
4	49	0.22	365	5,392	10,378	10,357
5	32	0.12	70	4,931	11,506	10,765
6	56	0.12	98	5,405	10,083	9,891
7	95	0.05	76	4,056	10,585	10,803
8	46	0.04	48	3,593	10,995	10,524
9	37	0.14	37	4,078	11,099	10,710
10	80	0.11	454	5,592	10,576	10,142
11	76	0.25	187	5,301	10,080	10,134
12	76	0.05	28	3,318	10,875	10,377
13	54	0.30	2,293	6,586	10,151	10,332
14	42	0.14	172	4,183	11,338	10,645
15	42	0.12	313	3,932	11,113	10,714
16	60	0.20	394	4,146	10,721	10,442
17	57	0.19	222	4,611	11,785	11,174
18	33	0.48	2,346	6,518	10,509	9,724
19	12	0.00	0	2,377	10,374	10,556
20	51	0.18	289	4,724	10,374	10,424

Note: This table shows summary statistics for the financial data from the Public Education Information Management System (PEIMS) public financial data from 2017 across Education Service Center (ESC) Regions. The values are calculated by summing the relevant financial figures across all districts within each region and then dividing by the total number of students in that region.

across 17 out of 20 regions, reflecting the criteria for being subject to the recapture policy.

However, for other financial variables, significant within-region differences are observed in a limited number of cases. Specifically, only 6, 3, and 4 regions show significant distinctions in total enrollment numbers, operational revenue per student and payroll per student, respectively. In these regions, recaptured districts tend to have fewer students, higher operational revenue per student, and higher payroll per student compared to non-recaptured districts.

The lack of significant differences in most regions provides us with confidence to use regions as our primary market units. This relative uniformity suggests that, aside from local tax revenue, recaptured and non-recaptured districts within the same region share similar financial characteristics. However, we must remain cautious and account for within-region variance.

TABLE 3. Financial Differences Between Recaptured and Non-Recaptured Within Regions

REGION	Enrollment Difference (n_students)	Local Tax Rev. p/ Student ($)	Operations Rev. p/ Student ($)	Payroll p/ Student ($)
1	-10,668.24***	11,757.85	7,583.04	2,570.31
2	-1,571.72	8,035.76***	7,088.72	3,121.01*
3	-1,139.65*	4,961.55***	1,642.05	677.48
4	6,428.47	4,097.47***	1,289.85*	405.99*
5	-442.04	5,873.57	2,483.89	1,178.15
6	418.57	3,343.23***	-6.62	27.36
7	-460.66	5,029.81***	1,894.54	1,072.15
8	-359.75	5,255.43***	-490.87	-75.75
9	-952.56**	5,775.15***	912.45	858.61
10	9,346.21	3,899.02***	-451.85	183.33
11	-5,511.61**	3,842.51***	402.84	164.74
12	-1,182.79	4,938.24**	-115.47	343.29
13	6,532.86	2,397.20***	-521.33	180.37
14	-559.5	5,964.94***	9,398.56**	2,444.07*
15	-882.37*	5,280.03***	1,271.74	1,016.05
16	-1,162.85	5,560.04***	2,349.46	2,101.68*
17	-1,137.85	8,752.28***	5,335.46**	2,302.98
18	-311.9	5,264.34***	-3,267.16	-3,990.55
19	N/A	N/A	N/A	N/A
20	-7,829.46**	7,582.06***	3,760.82	1,183.08

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows financial differences per student across regions, comparing figures between recaptured and non-recaptured districts. Data is sourced from the Public Education Information Management System (PEIMS) for 2017. Each value represents the average financial difference per student within regions.

3.2. PUMS - Labor Supply Data

The American Community Survey (ACS) Public Use Microdata Sample (PUMS) dataset serves as a pivotal component of our analysis. The ACS PUMS dataset is representative of the population, utilizing weighted microdata to ensure accurate reflections of demographic and economic characteristics across the whole United States. In our study, we utilize both market variables and individual characteristics from the PUMS dataset. To maintain focus on relevant educational and labor market dynamics, we restrict our sample to individuals with at least an associate degree. This criterion ensures that our analysis pertains to a suitably qualified population, whether they are teachers or in other professions.

We distinguish teachers within the dataset using the ACS Occupation Codes (OCC).[1]. Non-teachers are categorized as all other occupations, provided they also meet the associate degree requirement. Table 4 presents descriptive statistics for the final sample, highlighting key differences between teachers and non-teachers. The average wage for non-teachers is significantly higher at 73,269 compared to 50,449 for teachers. However, the wage variability is also much greater among non-teachers.

The data reveals that the teaching profession is predominantly composed of women, with 71% of teachers being female compared to 46% in non-teaching occupations. Additionally, a higher proportion of teachers are white 81% compared to non-teachers 73%. Teachers also have shorter average commute times (21 minutes) compared to non-teachers (25 minutes). Regarding marital status, the frequency of married individuals is slightly higher among teachers (65%) compared to non-teachers (63%).

Table 5 provides a detailed comparison of wages across different regions in Texas, revealing significant variability in the number of workers and wage differences between teachers and non-teachers. Four of the top five cities in population size—Houston (Region 4), Dallas (Region 10), Austin (Region 13), and Fort Worth (Region 11)—are located in regions that demonstrate a noticeable disparity in wages between teachers and other occupations. Notably, these regions show some of the largest wage gaps, underscoring the difference in how teachers are compensated relative to other professions in these urban areas.

Interestingly, the salary variations for teachers across different regions are much less pronounced compared to non-teaching occupations. Teacher salaries appear relatively constant, whereas non-teaching wages show significant regional differences. This constancy in teacher salaries might be influenced by state-level policies and funding mechanisms

[1]Specifically, we classify individuals under the following codes as teachers: ACS Occupation Codes used: 2200 - Postsecondary Teachers, 2300 - Preschool and Kindergarten Teachers, 2310 - Elementary and Middle School Teachers, 2320 - Secondary School Teachers, 2330 - Special Education Teachers, 2340 - Other Teachers and Instructors.

TABLE 4. Descriptive Statistics for Teachers and Non-Teachers

Variable	Teacher	Mean	Std. Dev.	Min.	Max.
wage	no	73,269	43,852	4	212,707
wage	yes	50,449	22,767	42	211,638
hours	no	43.41	9.51	20	99
hours	yes	43.95	10.09	20	99
50 weeks or more worked	no	0.90	0.3	0	1
50 weeks or more worked	yes	0.81	0.4	0	1
age	no	42.27	12.54	18	92
age	yes	42.54	12.50	20	92
commute	no	25.51	21.97	0	160
commute	yes	20.86	18.58	0	160
woman	no	0.46	0.50	0	1
woman	yes	0.71	0.45	0	1
white	no	0.73	0.44	0	1
white	yes	0.81	0.39	0	1
married	no	0.63	0.48	0	1
married	yes	0.65	0.48	0	1

Note: This table shows summary statistics using data from the Public Use Microdata Sample (PUMS) from 2017. The table summarizes market and demographic characteristics for teachers and non-teachers. The sample includes individuals with at least an Associate Degree and positive wages. The data is weighted, and the values presented in the table reflect these weights.

TABLE 5. Comparison of Wages by Region

REGION	Non-Teacher N	Teacher N	Non-Teacher Mean Wage	Teacher Mean Wage	Difference
1	77,762	35,544	57,488	50,493	-6,995***
2	31,114	8,137	66,544	48,839	-17,705***
3	23,913	7,135	70,200	48,912	-21,288***
4	693,956	111,320	79,262	52,511	-26,750***
5	23,797	6,204	70,589	45,729	-24,860***
6	95,915	24,178	73,591	50,647	-22,944***
7	59,734	18,119	63,241	45,844	-17,397***
8	14,051	4,625	61,992	45,137	-16,855***
9	18,019	5,622	61,260	47,432	-13,828***
10	552,158	77,830	76,521	50,609	-25,912***
11	368,860	65,325	74,743	52,503	-22,241***
12	59,645	16,193	63,540	50,381	-13,159***
13	353,989	50,944	73,104	48,143	-24,960***
14	19,012	5,402	56,693	43,959	-12,734***
15	13,359	3,878	56,967	44,129	-12,838***
16	27,915	7,525	66,172	46,606	-19,566***
17	32,635	10,048	60,630	49,472	-11,157***
18	22,587	5,470	73,650	50,538	-23,112***
19	67,252	18,751	59,573	47,952	-11,621***
20	227,388	45,207	67,612	51,764	-15,848***
Sum	2,783,061	527,457	-	-	-

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows summary statistics using data from the Public Use Microdata Sample (PUMS). The table compares wages between teachers and non-teachers across different Education Service Center (ESC) Regions. The sample includes individuals with at least an Associate Degree and positive wages. The data is weighted, and the values presented in the table reflect these weights.

designed to maintain equitable pay for educators. In contrast, disparities in non-teaching wages may be due to differences in industry composition across regions, varying cost of living expenses, the intensity of human capital, and the competitiveness of the job market in certain areas.

TABLE 6. Regression Results

	Dependent variable:			
	ln wage hour			
	(1)	(2)	(3)	(4)
Age	0.073***	0.071***	0.071***	0.071***
	(0.001)	(0.001)	(0.001)	(0.001)
Age^2	–0.001***	–0.001***	–0.001***	–0.001***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Distance to Work	0.002***	0.002***	0.002***	0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Married	0.160***	0.150***	0.153***	0.150***
	(0.003)	(0.003)	(0.003)	(0.003)
Woman	–0.157***	–0.154***	–0.153***	–0.154***
	(0.003)	(0.003)	(0.003)	(0.003)
White	0.040***	0.055***	0.088***	0.054***
	(0.004)	(0.004)	(0.004)	(0.004)
Teacher	–0.078***	–0.091***	–0.073***	–0.033***
	(0.004)	(0.004)	(0.004)	(0.009)
Region Recapture				0.319***
				(0.019)
Recapture x Teacher				–0.303***
				(0.044)
Constant	1.499***	1.498***	1.322***	1.437***
	(0.018)	(0.018)	(0.020)	(0.018)
School Dummies	*NO*	*YES*	*YES*	*YES*
Region Dummies	*NO*	*NO*	*YES*	*NO*
Observations	165,192	165,192	165,192	165,192
R^2	0.115	0.132	0.146	0.133
Adjusted R^2	0.115	0.132	0.146	0.133
Residual Std. Error	2.827 (df = 165184)	2.801 (df = 165181)	2.778 (df = 165162)	2.798 (df = 165179)
F Statistic	3,081.191*** (df = 7; 165184)	2,510.520*** (df = 10; 165181)	972.632*** (df = 29; 165162)	2,119.100*** (df = 12; 165179)

Note: *p<0.1; **p<0.05; ***p<0.01. This table shows regression results using data from the Public Use Microdata Sample (PUMS). Dependent variable: log wage per hour. The specifications are as follows: (1) includes variables such as age, age squared, distance to work, marital status, gender, race, and teacher status; (2) adds school dummy variables; (3) introduces regional dummy variables; (4) combines both school and regional dummy variables; and (5) replaces regional dummies with the percentage of districts subject to recapture and its interaction with the teacher variable. All regressions were weighted to ensure that the estimates reflect the population accurately.

Despite Region 4 exhibited the highest average salaries for teachers in Texas, it also exhibited the largest wage disparities compared to other occupations within the state. This might indicate an attempt to compensate teachers for the opportunity costs associated with their profession in these regions. However, the magnitude of wage gaps suggests that this strategy has not been entirely effective. It is not easily verifiable whether regions that transfer more through recapture are the ones that pay higher salaries for teachers. For instance, Region 18, where 48% of its districts are subject to recapture, offers some of the highest teacher wages in Texas. Conversely, Region 3, with 39% of its districts subject to recapture, ranks tenth in terms of average teacher salary.

The regressions in Table 6 seek to bridge this gap by isolating the effect of each variable on salaries. The analysis reveals that being a teacher is associated with significantly lower wages. Specifically, the teacher coefficient of -0.078 in the first specification indicates that teachers earn approximately 7.8% less per hour compared to non-teachers. In the second specification, adding school levels dummy variables further impacts the teacher coefficient, increasing the negative effect to -0.091. This suggests that accounting for differences across individuals schooling levels exacerbates the observed wage penalty for teachers. The third specification adds regional controls to the regression.

Finally, specification 4 replaces the regional dummies with the percentage of districts subject to recapture and its interaction with the teacher variable. The coefficient for the interaction term between recapture percentage and teacher status is -0.303, indicating that the negative effect of being a teacher almost entirely offsets the benefits of being in a recapture region (0.319).

3.3. The Education Research Center (ERC)

The Texas Education Research Center (ERC) serves as a central data repository, facilitating access to longitudinal, student-level data for research. Through this center, researchers can merge datasets from various agencies, following students in Texas from the time they enroll in school until their labor market outcomes are observable. By providing access to data from multiple sources, the ERC enables detailed longitudinal analyses of educational and labor market trajectories.

The data available through the ERC include records from the Texas Education Agency (TEA) and the Texas Higher Education Coordinating Board (THECB), providing a comprehensive view of students' academic performance. For this study, we focus on the average scores of students who took both the English I and Algebra I STAAR exams in the same year. These exams assess critical skills in reading, writing, and mathematics. We standardize the test scores to have a mean of zero and a standard deviation of one, ensuring comparability

TABLE 7. Students Characteristics by Region

REGION	Enrollment (n)	White (%)	Disadvantaged (%)	Talented (%)	ESL (%)	MATH + ENG (std score)
1	19,565	0.011	0.862	0.058	0.242	-0.067
2	6,012	0.172	0.648	0.022	0.019	-0.028
3	3,445	0.291	0.617	0.026	0.038	-0.146
4	58,519	0.189	0.623	0.023	0.095	0.025
5	4,479	0.059	0.559	0.002	0.027	0.027
6	7,100	0.169	0.609	0.015	0.065	-0.016
7	10,030	0.504	0.611	0.038	0.055	-0.021
8	3,328	0.562	0.611	0.057	0.037	0.083
9	2,371	0.589	0.564	0.037	0.038	0.041
10	29,311	0.267	0.528	0.070	0.124	0.139
11	27,559	0.390	0.529	0.033	0.095	0.098
12	9,450	0.376	0.587	0.020	0.060	-0.017
13	17,264	0.333	0.531	0.024	0.105	-0.019
14	3,100	0.338	0.609	0.015	0.058	0.017
15	3,100	0.243	0.564	0.033	0.031	0.034
16	4,666	0.428	0.613	0.016	0.035	0.034
17	3,102	0.283	0.538	0.018	0.072	-0.037
18	10,592	0.038	0.731	0.013	0.156	-0.045
19	4,490	0.088	0.637	0.034	0.160	-0.113
20	24,834	0.165	0.647	0.026	0.062	-0.092

Note: This table reflects high school students who took the English I and English II STAAR tests. The Education Research Center (ERC) and Texas Education Agency (TEA) classify students as disadvantaged based on economic criteria, while talented students are identified through academic performance and aptitude. ESL represents students classified as English as a Second Language.

and facilitating interpretation across subjects.

Within the TEA and ERC context, students are classified as *disadvantaged* based on economic criteria, such as eligibility for free or reduced-price lunch programs. *Talented* students are identified through academic performance indicators and aptitude assessments, typically including those who participate in gifted and talented programs. Additionally, students classified as *English as a Second Language* (ESL) are those who are non-native English speakers and receive specialized language instruction.

4. Model

The model focuses on a single sector: the Educational sector. However, workers have an alternative job opportunity in a general goods sector, where wages are determined competitively. In this framework, schools within the Educational sector set the skill rental price to maximize student achievement. The wages and labor supply in the Educational sector, along with student performance, are endogenously determined in a stationary equilibrium. Both potential workers and the education sector consider the government recapture policy as a given.

Our model consists of two stages that are solved sequentially but analyzed separately. In the first stage, school districts set skill prices to maximize student achievement, predicting the labor supply of teachers under rational expectations. In the second stage, workers decide to supply labor either in the educational sector or the general goods, or to stay home.

We assume there are M segregated markets, and the model is solved separately for each market.

4.1. 1st Stage - Educational Sector Problem

The educational sector production function in each region m considers that student scores depend on aggregate teaching skills and demographics. In this framework, school districts (in our case, regions) decide how much to pay their teachers by choosing the price of skill r_m, thus allocating resources between expenditures on materials and investing in teachers' total skills (S_m). To solve their problem, schools in each region maximize average achievement $\mathbb{E}[E_m]$, subject to the achievement production function (E_m) and budget constraint. The budget constraint consists of the revenue provided by the federal government (F_m), state transfers (T_m), and property taxes (P_m), while expenses consist of wages paid to teachers (W_m), other types of expenditures like materials and services (C_m), and their

recapture transfers to the state (R_m). Hence, the educational firms deal with the following problem:

$$\max_{r} \quad \mathbb{E}[E_m] \tag{1}$$

$$\text{s.t.} \quad E_m = \beta_0 + \beta_1 S_m + X_m \tag{2}$$

$$F_m + T_m + P_m = W_m + C_m + R_m \tag{3}$$

In equation (2), X_m represents a vector of demographic variables, including proportions of female students, racial compositions, and economic disadvantage, among others.

School districts anticipate the effects of changes in skill rental prices r_m on the labor supply of teachers in the subsequent stage. This implies that schools take the teacher supply function as given. Moreover, we assume the number of students in a region is fixed. Changes in the skill rental price r_m induce adjustments in the wage offer function for teachers, which affects both the supply of skills S_m and the costs of teachers W_m.

4.2. 2nd Stage - Labor Supply

We model the labor supply decisions of individuals using a Roy model of occupational choices. Each individual i is characterized by a set of observable characteristics such as age, education, gender, and ethnicity.

There are three choices available for individuals: work as a teacher in the Educational Sector (E); work in the Non-Educational Sector (NE); or stay at home (H). The choice-specific utility functions for each sector are given by:

$$u_{i,m,E} = \ln w_{i,m,E} + \delta_{0,E} + \delta_{1,E}\text{Woman}_i + \delta_{2,E}\text{Ethnicity}_i + \text{Married}_i, \tag{4}$$

$$u_{i,m,NE} = \ln w_{i,m,NE}, \tag{5}$$

$$u_{i,m,H} = \delta_{0,H} + \delta_{1,H}\text{Woman}_i + \delta_{2,H}\text{Ethnicity}_i + \delta_{3,H}\text{Married}_i + \delta_{4,H}\text{Age}_i. \tag{6}$$

In these utility functions, $w_{i,m,j}$ denotes the wage offer to individual i in market m for sector $j \in \{E, NE\}$. The parameters δ capture nonpecuniary aspects of utility. Individuals make their occupational choice by maximizing their utility over the available options. Specifically, each individual compares the utility from working in the educational sector, the non-educational sector, and staying at home, and chooses the option that provides the highest utility.

Individuals are endowed with skills relevant to both the educational and non-educational sectors, determined by observable characteristics like age and education. Sector-specific random shocks ε_i also impact the wage offers.

The wage offers from both sectors are functions of the individual's observable characteristics and experience. The wage offer equations are given by:

$$w_{i,m,E} = r_m \exp\left(X_i \lambda_E + \varepsilon_i^E\right), \tag{7}$$

$$w_{i,m,NE} = \exp\left(X_i \lambda_{NE} + \varepsilon_i^{NE}\right). \tag{8}$$

Here, r_m is the rental price of teaching skills in market m, X_i represents the vector of observable characteristics of individual i, λ_E and λ_{NE} are the coefficients for these characteristics in the educational and non-educational sectors, respectively, and ε_i^E and ε_i^{NE} are sector-specific random shocks.

4.3. Identification of the Skill Rental Price r_m

The identification of the skill rental price r_m is grounded in the observed variations across markets in both the supply of teaching labor and the demand for educational outcomes. On the supply side, individuals make occupational choices among teaching, non-teaching employment, and home production based on wage offers and non-pecuniary factors. These choices, along with observable characteristics and wage data from both sectors, inform how changes in r_m influence the supply of teaching skills S_m in each market m.

On the demand side, school districts aim to maximize student achievement while adhering to budget constraints that include revenues from federal and state transfers, property taxes, and recapture payments. The districts decide on r_m to allocate resources optimally between teacher salaries and other educational expenditures. The achievement production function, which relates student outcomes to aggregate teaching skills S_m and demographic factors X_m, provides a link between the skill rental price and educational performance.

Identification of r_m arises from exogenous variations in market characteristics that affect either the supply or demand for teachers but are independent of unobserved cost shocks in the educational sector. For example, differences in wages in the non-educational sector across markets influence individuals' decisions to become teachers without directly affecting the educational sector's optimization problem. Similarly, variations in student demographics and funding levels across markets alter the districts' demand for teaching

skills, as they impact the marginal benefit of investing in teacher quality.

By leveraging these exogenous variations, we observe how changes in market conditions lead to adjustments in the equilibrium skill rental price r_m. The structural model, along with the parameters estimated from the labor supply decisions, allows us to isolate the effect of r_m on both the supply of teaching skills and the districts' achievement maximization problem. Assuming that unobserved factors affecting the educational sector's costs are uncorrelated with the exogenous market characteristics, we can confidently identify r_m based on observed data on wages, occupational choices, and educational outcomes across different markets.

4.4. Equilibrium

An equilibrium in this model is defined as a vector of rental prices for the Educational sector r_m and optimal occupational choices d^*, satisfying the following conditions: (i) the aggregate demand for teachers equals the aggregate supply of teachers, and (ii) given r_m, d^* represents the optimal occupational choice for each individual. Individuals receive wage offers from both sectors, which depend on their observable characteristics and the current rental price in the educational sector. They then decide their sector of employment by maximizing their utility over the available options. The wage offer in the non-educational sector is a function of the individual's skills in that sector, while in the educational sector, it depends on the rental price r_m and the individual's observable characteristics.

Schools in each region aim to maximize educational production, which is a function of student baseline ability, teachers' total skills, and school's materials, subject to budget constraints, wages paid to teachers, costs of capital, and transfers to the state.

Definition 1. An equilibrium in a market m is (r_m, d^*) such that:

(a) r_m is such that the aggregate demand for teachers equals the aggregate supply of teachers.

(b) Given r_m, d^* is the optimal occupational choice for every individual.

4.5. Solving the Model

To solve this model numerically, we start by establishing an initial value for the rental price of teaching skills for each market. With this, we simulate individuals' occupational choices, calculating the utility for each option and incorporating individual-specific random shocks. Individuals select the occupation with the highest utility. Those who choose teaching contribute their skills to the educational sector, where we calculate the aggregate teaching

skills supply by summing their skill levels. This total supply directly impacts average student achievement, which is maximized by the educational sector within a set budget. The budget constraint is critical as it limits total expenditure on teacher salaries. To find the optimal rental price that maximizes student achievement within budget, we frame the problem as a constrained optimization, where the total wage bill must not exceed the budget. Using numerical methods, we iteratively adjust the rental price, re-simulating choices to achieve an equilibrium where the educational sector's demand for teaching skills aligns with the supply, all within budgetary limits.

5. Estimation

We estimate the model separately for each market using a two-step procedure. In the first step, we estimate the parameters of the second stage of the model, ϕ_2. These are the preferences parameters of the labor supply decision. These parameters include the rental skill prices r_m. In the second step, we take the estimates of rental prices, $\hat{r}_m$, as given. The target of the second stage is to rationalize these recovered rental prices as coming from the constrained maximization problem of school districts. The parameters needed are those related to the achievement production function, which we call ϕ_1.[2]

In both steps, we estimate the parameters by Method of Simulated Moments (MSM).[3] We, therefore, retrieve the set of initial conditions for a subset of individuals and several empirical moments related to the model. This approach allows the simulation of the set of individuals starting from their initial conditions.

The MSM's objective is to minimize the weighted difference between empirical and simulated moments with respect to the unknown set of structural parameters ϕ. Let M_D denote the vector of moments calculated from the observed data, and $M_{S,R_N}(\phi)$ denote the vector of moments derived from R_N simulated samples of size N, where we make clear the dependence of the simulated moments to the structural parameters.[4] The minimization problem is:

[2]This estimation strategy is inspired by Tincani (2021).

[3]We do so because the ERC servers, where part of the data resides, are not high-performance computing machines, and we cannot retrieve an entire data set containing all the information needed to estimate the parameters through maximum likelihood.

[4]For a given simulated sample r, let ζ_r denote the sequence of shocks $\{\varepsilon_{s,m}, \xi_{s,m}\}$ for $s = 1, \ldots, N$, and $m = 1, \ldots, M$ the vector of moments. We define $M_{S,N}(\phi) = \frac{1}{R_N} \sum_{r=1}^{R_N} M_{S,r}(\phi, \zeta_r)$. Note that ζ_r remains fixed throughout the estimation procedure to avoid noise in the objective function.

$$\hat{\phi} = \arg\min_{\phi}(M_D - M_{S,R_N}(\phi))' W (M_D - M_{S,R_N}(\phi)),$$

where W is a positive definite weighting matrix.[5]

5.1. First step - Labor Supply

We calculate a total of 1060 moments, focusing on four key dimensions across regions: choice frequency, earnings averages, earnings standard deviations, and linear probability models of occupational choices. We analyze the fraction of individuals in each of the three sectors (teacher, non-teacher, home production), compute the log earnings and their standard deviation for each sector, and estimate linear probability models to capture the likelihood of choosing each occupation. These moments provide the necessary data for estimating the model to observed patterns in labor market choices and wage distribution.

- **Choice Frequency**:
  - The fraction of individuals in each of the three sector categories for each region (teacher, non-teacher, home).
  - Total of 60 moments.
- **Earnings for Each Period**:
  - Average log earnings and standard deviation of log earnings for each sector.
  - Total of 120 moments.
- **Linear Probability Models**:
  - Linear probability models for each decision (teacher, non-teacher, home) across different regions.
  - Total of 840 moments.

5.2. Second Step - Educational Sector

We calculate a total of 1,200 moments related to the test scores E_m to estimate the parameters of the educational sector model. These moments focus on two key dimensions across

[5]The consistency and asymptotic properties of these kind of estimators are discussed in Gourieroux, Monfort, and Renault (1993).

regions: test score distributions by demographic subgroups, and the quantiles of the test score distributions to understand the dynamics and student composition in each region.

- **Test Scores by Demographic Subgroups**:
  - We compute the mean and standard deviation of test scores for each possible combination of demographic characteristics, including gender (male, female), race/ethnicity (White, Black, Asian, Other), and economic disadvantage status (disadvantaged, not disadvantaged).
  - This results in various subgroups, such as female students who are White and economically disadvantaged, male students who are Black and not economically disadvantaged, etc.
  - Across all possible combinations and regions, we obtain a total of 400 moments.
- **Quantiles of Test Score Distributions**:
  - We compute the mean test score and the number of individuals within 20 quantiles of the test score distribution for each region.
  - This approach captures the distributional characteristics and heterogeneity in student achievement across regions.
  - This adds an additional 800 moments to our analysis.

6. Results

6.1. Model Estimates and Model Fit - Labor Supply

The parameter estimates from our model provide insights into the labor supply decisions of individuals choosing between working as a teacher, working in the general goods (other) sector, or staying at home. Table 8 presents these estimates, segregated into pecuniary (Panel A) and non-pecuniary (Panel B) components of the utility functions for each occupational choice. The pecuniary parameters capture how wage offer influences utility, while the non-pecuniary parameters reflect the impact of individual characteristics such as gender and ethnicity on the utility derived from each option.

In Panel A of Table 8, the wage offer parameters indicate that wages positively affect the utility of choosing an occupation in both the non-educational and teaching sectors. The return to a graduate degree is substantially higher in the teaching sector (0.529) compared to the non-educational sector (0.002), suggesting that advanced education is

TABLE 8. Model Estimates - Labor Supply

	Others		Teacher		Home	
Wage Offer						
	Param.	S.E.	Param.	S.E.	Param.	S.E.
Constant	11.485	0.141	10.057	0.053		
Age	-0.028	0.001	-0.017	0.001		
Grad. Degree	0.002	0.001	0.529	0.042		
$log(\sigma_\varepsilon)$	-0.022	0.003	-0.069	0.014		
Non-Pecunary Component						
Constant	-	-	-0.302	0.041	2.177	0.086
Woman	-	-	1.609	0.101	0.009	0.0
White	-	-	0.102	0.025	1.107	0.044
Asian	-	-	-4.005	1.175	-0.628	0.035
Other	-	-	-0.358	0.108	1.448	0.112
Married	-	-	-1.1	0.077	-0.129	0.008
Age	-	-	-	-	-0.711	0.023

Note: This table shows parameters estimates and standard errors from the 1st stage of the model. Coefficient units outside the wage offer functions is $10,000. Estimates from 20 markets with an average of 12,454 workers in each market. The constant from the Others sector varies by market, so we report the average here. Omitted category in Ethnicity dummies is African American.

more valued in teaching professions. The negative coefficients on age imply that wage offers decrease slightly with age in both sectors, potentially reflecting age-related preferences or discrimination.

Panel B presents the non-pecuniary utility parameters. For the teaching profession, being female significantly increases utility (1.609), indicating that women are more likely to choose teaching, possibly due to factors like work-life balance or social norms. The negative coefficient on "Married" (-1.100) suggests that married individuals derive less utility from teaching. Ethnicity also influences utility: being White increases the utility of choosing teaching (0.102), while being Asian decreases it significantly (-4.005).

For the home production choice, the positive constant (2.177) indicates a base level of utility associated with staying at home. Age negatively affects utility (-0.711), which might be related to the way we constructed the home variable, following Keane and Wolpin (1997), individuals were classified as "home production" if they worked less than 27 weeks per year and less than 20 hours per week. Since younger individuals are more likely to have part-time or non-full-time work, this might explain the negative relationship with age. Being White or of "Other Ethnicity" increases the utility of staying at home when

TABLE 9. Model Estimates - Labor Supply - Market Varying

	Others Constant		**Teacher** Log Skill Rental Prices	
	Param.	S.E.	Param.	S.E.
Market 1	11.289	0.115	0.0	0.0
Market 2	11.513	0.202	-0.101	0.006
Market 3	11.462	0.147	-0.089	0.048
Market 4	11.701	0.08	-0.245	0.035
Market 5	11.525	0.138	-0.08	0.024
Market 6	11.446	0.133	0.0	0.056
Market 7	11.356	0.115	-0.15	0.01
Market 8	11.353	0.291	-0.016	0.044
Market 9	11.449	0.148	-0.03	0.006
Market 10	11.739	0.071	-0.285	0.033
Market 11	11.677	0.081	-0.214	0.03
Market 12	11.383	0.109	-0.139	0.069
Market 13	11.648	0.073	-0.385	0.03
Market 14	11.333	0.189	-0.198	0.018
Market 15	11.357	0.246	-0.138	0.042
Market 16	11.472	0.101	-0.079	0.053
Market 17	11.404	0.203	-0.058	0.026
Market 18	11.585	0.172	-0.013	0.07
Market 19	11.459	0.084	-0.131	0.074
Market 20	11.549	0.124	-0.269	0.029

Note: This table shows parameters estimates and standard errors from market varying parameters from the labor supply model. Estimates from 20 markets with an average of 12,454 workers in each market. Log skill rental prices normalized to 0.0 for Market 1.

compared to African Americans, whereas being Asian decreases it.

Table 9 provides the market-specific constants for the non-educational sector and the estimated log skill rental prices for the teaching sector across the 20 markets. These parameters capture regional variations in wage levels and the valuation of teaching skills. The constants for the non-educational sector vary across markets, reflecting regional differences in wage levels due to factors such as cost of living and local economic conditions. The log skill rental prices for the teaching sector are generally negative, indicating that relative to Market 1, other markets offer lower rental prices for teaching skills. Notably, Market 13 has the lowest skill rental price (-0.385), suggesting that schools in this market place a lower value on teaching skills in wage determination.

The wealthier regions, including Markets 4, 10, 11, and 13, home to major cities like Houston, Dallas, Fort Worth, and Austin, exhibit an intriguing labor market dynamic.

These markets simultaneously feature the highest pay for non-teaching occupations and the lowest skill rental prices for teaching. This disparity suggests that the opportunity cost of choosing teaching in these affluent regions is significantly higher due to more lucrative alternatives in the non-educational sector. Additionally, the lower valuation of teaching skills may reflect a labor market imbalance where wealthier districts can attract and retain teachers despite offering relatively lower returns on skills.

Figures 4 and **??** in Appendix B display simulations from the first step of the model using the estimated parameters and compare them with actual data, showing the model fit for the labor supply stage of the model. Overall, the model successfully captures the observed patterns in occupational choices and wage distributions. Specifically, it reflects the choices proportion among the three available options: working in the educational sector, the general goods sector, or staying at home. Additionally, it captures the wage structures for both the educational and general goods sectors, aligning well with empirical data. These patterns hold consistently across each of the 20 regions, demonstrating the model's robustness in representing regional differences in occupational choices and wage distributions.

6.2. Model Estimates and Model Fit - Educational Sector

Table 10 presents the estimates of the educational production function, which models student achievement as a function of teacher skills and student characteristics. The parameters capture how these factors contribute to educational outcomes.

The coefficient on $\log(S)$, representing the log of aggregate teacher skills, is positive and significant (0.036), indicating that higher total teaching skills in a market contribute to improved student achievement. The demographic variables show that female students perform better on average, as do students who are White or Asian. Being economically disadvantaged has a negative impact on achievement, consistent with existing literature on the socioeconomic determinants of education.

Figure 6 in Appendix B compares the simulated average test scores with the actual data across markets. The model closely matches the observed test scores, suggesting that it accurately captures the key determinants of student achievement.

Table 11 presents the estimated market-specific constants from the achievement function across the 20 markets. These constants represent the baseline level of student achievement in each market, after controlling for aggregate teacher skills and student demographic characteristics. The variation in these constants reflects regional differences in unobserved factors affecting student achievement.

TABLE 10. Model Estimates - Educational Sector

	Param.	S.E.
Constant	-0.237	0.012
$log(S)$	0.036	0.007
Woman	0.312	0.0
White	0.441	0.001
Asian	0.774	0.001
Other	0.205	0.001
Econ. Disad.	-0.394	0.001
$log(\sigma_\xi)$	-2.763	0.027

Note: This table shows parameters estimates and standard errors from the education sector model. The constant is allowed to vary by market, and we report the average estimates.

Examining the table, we observe significant heterogeneity in the estimated achievement constants across markets. However, these differences should not be interpreted as direct evidence that one region inherently achieves higher or lower baseline levels of student achievement compared to another. The observed coefficients for demographic characteristics also play a critical role in determining the overall level of achievement in each market. This suggests that the variation in constants reflects complex interactions between unobserved regional factors and the demographic composition of students, rather than simply indicating regional disparities in achievement.

6.3. Counterfactuals

To evaluate the impact of the recapture policy on the teacher labor market, we conduct a counterfactual analysis where we eliminate recapture payments, setting them to zero and adjusting the budgets of each market accordingly. Then, we simulate the model and compute the changes in the percentage of workers choosing the teaching sector and their skill distribution against the baseline scenario.

Implementing this counterfactual requires simulating the new budget constraints for each market. The budget constraint for market m is given by:

$$F_m + T_m + P_m = W_m + C_m + R_m,$$

where F_m are federal transfers, T_m are state transfers, P_m are local property taxes, W_m is the total wage bill for teachers, C_m represents materials and other educational

TABLE 11. Model Estimates - Achievement Function Constants

	Achievement Constant	
	Param.	S.E.
Market 1	-0.155	0.014
Market 2	-0.203	0.008
Market 3	-0.336	0.007
Market 4	-0.222	0.024
Market 5	-0.198	0.005
Market 6	-0.303	0.014
Market 7	-0.234	0.012
Market 8	-0.137	0.005
Market 9	-0.249	0.006
Market 10	-0.24	0.023
Market 11	-0.267	0.021
Market 12	-0.269	0.013
Market 13	-0.342	0.02
Market 14	-0.146	0.006
Market 15	-0.249	0.003
Market 16	-0.159	0.009
Market 17	-0.207	0.009
Market 18	-0.439	0.003
Market 19	-0.075	0.011
Market 20	-0.316	0.019

Note: This table shows parameters estimates and standard errors from market varying parameters from the achievement function.

expenditures, and R_m is the recapture payment. By setting $R_m = 0$, markets that were net contributors to the recapture system retain more funds, while others receive reduced state transfers. Federal transfers and local taxes are not affected by the policy, only state transfers.

Unfortunately, there is no detailed information about state sharing rules that can be implemented in such a stylized model, so we implement a simple sharing rule where the markets that pay the most of the recapture get their money back, at the cost of the other markets. Markets 4, 10, 13, and 18 together cover about 75% of the total recapture payments. These markets contain the cities of Houston, Dallas-Fort Worth, Austin, and the resource-rich Permian Basin area, respectively. We subtract this extra budget equally across the other markets.

In practice, what this counterfactual policy does is to allow markets that increase their net budget to increase their optimal skill price r_m^*. On the other hand, the markets that lose

portions of their budget must decrease their optimal skill price r_m^*. This in turn will affect their ability to hire teachers. We focus on two representative markets: Market 1, which loses budget under the policy change, and Market 13, which gains budget.

Market 1, located in the southern border of Texas, has both the highest rental price r_m and the lowest constant in the Goods market, indicating a low base pay in the outside option. On the other hand, Market 13, which includes Austin ISD and is the market with the largest recapture payments, has a high paying Goods market, and values skill teachers the lowest.

TABLE 12. Counterfactual Recapture - Percent Changes

	Net Revenue	r_m^*	Teachers	$\sum_i s_i$	$\bar{s_i}$
Market 1	-3.7%	-1.9%	-2.3%	-0.7%	1.7%
Market 13	19.8%	28.6%	44.6%	16.9%	-19.2%

Note: This table shows the impact of a counterfactual Recapture policy where the 4 markets that pay 75% of the total recapture equally receive the total recapture back, at the cost of the other 16 markets. Market 1 is a net loser, while Market 13 is a net gainer of budget.

Table 12 summarizes the percentage changes in key variables resulting from the policy change. In Market 13, the elimination of recapture payments leads to a substantial increase in net revenue (19.8%), allowing the market to raise its skill rental price by 28.6%. This results in a 44.6% increase in the number of teachers hired. However, the average skill level of teachers decreases by 19.2%, as the higher rental price attracts more individuals with lower teaching skills into the profession. This outcome suggests a trade-off between the quantity and quality of teachers when budgets increase. Conversely, Market 1 experiences a reduction in net revenue (-3.7%) and a slight decrease in the skill rental price (-1.9%). The number of teachers decreases by 2.3%, but the average skill level increases by 1.7%, indicating that lower-skilled teachers are more likely to exit the profession when budgets are constrained.

To further understand these results, we examine the distribution of teaching skills in both markets. Figure 2 shows the baseline density of estimated teaching skills for individuals employed in the teaching and non-educational sectors in Markets 1 and 13. In both markets, the skill distribution of those employed in the teaching sector is higher compared to the non-educational sector. Interestingly, even though Market 13 offers a lower skill rental price at baseline, its teaching sector's skill distribution dominates that of Market 1. This suggests that Market 13 attracts higher-skilled teachers despite offering lower wages.

In Figure 3, we plot the density of teaching skills for those employed in the teaching

sector under the baseline and counterfactual scenario. As shown in Table 12, we see a large shift to the left of the skill distribution in Market 13, and a very small shift to the right in Market 1. In Market 13, the skill distribution shifts noticeably to the left under the counterfactual policy, indicating that the additional teachers hired are, on average, less skilled. This mechanical effect occurs because the increased skill rental price attracts individuals from the lower end of the skill distribution into teaching. In Market 1, the skill distribution shifts slightly to the right, as the budget reduction leads to the exit of lower-skilled teachers, raising the average skill level among remaining teachers.

These results underscore the role of the recapture policy in promoting equity across educational markets. By redistributing funds from wealthier districts to those with fewer resources, recapture mitigates disparities in teacher hiring and skill distribution. In the baseline scenario with recapture in place, markets like Market 1 benefit from additional funds, enabling them to maintain higher skill rental prices and attract skilled teachers despite lower local revenues. Conversely, without recapture, affluent markets such as Market 13 can significantly boost their budgets and teacher numbers but at the cost of a decline in average teacher skill, as increased wages attract a broader pool of candidates, including less skilled individuals. This shift could widen the educational quality gap between affluent and less affluent regions. Therefore, the recapture policy is capable of fostering a more balanced educational landscape by ensuring that markets with limited fiscal capacity can retain skilled teachers and sustain their educational outcomes.

7. Discussion

In this paper, we developed a structural general equilibrium model to analyze the relationships between school funding, teacher compensation, and student achievement in Texas Independent School Districts. Our findings underscore the role of the state's recapture policy in promoting educational equity by redistributing resources from wealthier to less affluent districts. The policy not only affects the quantity of teachers that districts can hire but also has nuanced effects on teacher quality and student outcomes.

Our counterfactual analysis revealed that eliminating the recapture policy would allow wealthier districts to offer higher wages, thereby attracting more teachers. However, this influx could lead to a decrease in average teacher quality due to the entry of less-skilled individuals, potentially diluting educational outcomes. Conversely, less affluent districts might face budget cuts and a reduction in teaching staff but could experience an increase in average teacher quality as lower-skilled teachers exit. These results highlight the trade-offs inherent in school funding policies and emphasize the need for careful consideration of

both teacher quantity and quality in policy design.

The model we developed is significant in that it captures the general equilibrium effects of school funding policies on the teacher labor market and educational outcomes, incorporating features such as monopsonistic wage-setting and non-pecuniary job attributes. However, there is room for improvement. One potential enhancement is the inclusion of unobserved heterogeneity in individual teacher skills. By allowing for variation in teacher effectiveness that is not captured by observable characteristics, the model could more accurately reflect the impact of teacher quality on student achievement.

Further, our analysis could be extended by exploring additional counterfactual scenarios. For instance, we could examine alternative designs of the recapture policy that more precisely target funding disparities without unintended consequences on teacher quality. Implementing policies that incentivize high-skilled teachers to remain in or join less affluent districts could be another avenue. Additionally, considering the effects of introducing merit-based pay or professional development opportunities could provide insights into strategies for improving teacher quality across districts.

Moreover, incorporating dynamic elements into the model could capture the long-term effects of policy changes on the teacher labor market and student outcomes. This would allow for the examination of how teachers' career decisions evolve over time in response to policy shifts, and how these decisions, in turn, affect educational equity and efficiency in the long run.

In conclusion, our study contributes to a deeper understanding of the intricate dynamics between school funding, teacher labor markets, and educational outcomes. By highlighting the importance of considering both teacher quantity and quality, as well as the broader equilibrium effects of policy changes, we provide valuable insights for policymakers aiming to design effective and equitable education finance systems. Future research building on our model could further inform strategies to enhance educational outcomes while addressing disparities across districts.

Appendix A. Data

In this appendix, we provide a detailed breakdown of the key variables used in our model, explaining how each variable is defined, its corresponding data source, and the methodology used for computation. The variables are categorized into three main areas: labor supply, wage offers, and educational sector production. For labor supply, we focus on occupational choices and factors influencing these decisions, utilizing data from the ACS-PUMS. Wage offers are modeled for both the educational and non-educational sectors, accounting for individual characteristics and sector-specific shocks. Lastly, the educational sector production is defined through the combination of teacher skills, school budgets, and educational outcomes, derived from TEA Finance and ERC datasets. Each variable in the tables provided below reflects the essential components used for estimating our structural model.

Labor Supply

The labor supply decisions are modeled as follows:

$$
\begin{aligned}
u_{i,m,E} &= \ln w_{i,m,E} + \delta_{0,E} + \delta_{1,E}\text{Woman}_i + \delta_{2,E}\text{Ethnicity}_i + \delta_{3,E}\text{Married}_i, \\
u_{i,m,NE} &= \ln w_{i,m,NE}, \\
u_{i,m,H} &= \delta_{0,H} + \delta_{1,H}\text{Woman}_i + \delta_{2,H}\text{Ethnicity}_i + \delta_{3,H}\text{Married}_i + \delta_{4,H}\text{Age}_i.
\end{aligned}
$$

Variable	Description	Data Source	Methodology/Unit
d	Occupational choice indicator for individual i in market m; takes values indicating Teacher, Non-Teacher, or Home Production.	ACS-PUMS	Based on reported occupation and employment status. Home Production defined as working less than 27 weeks per year and less than 20 hours per week.

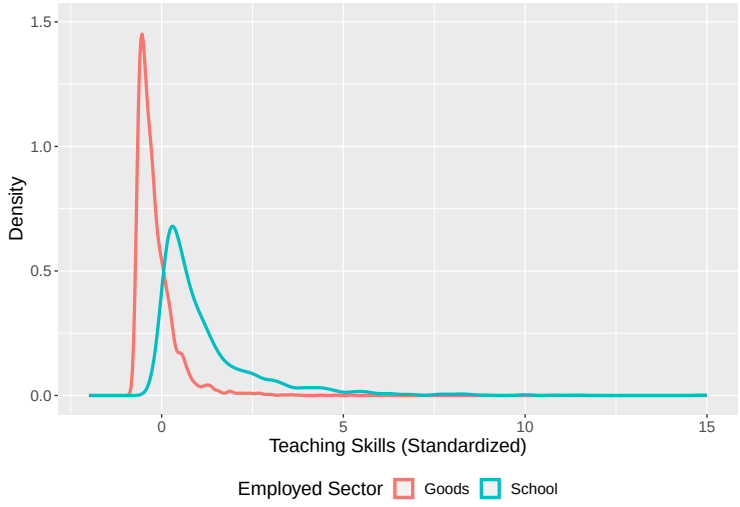
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TABLE 13 – *Continued from previous page*

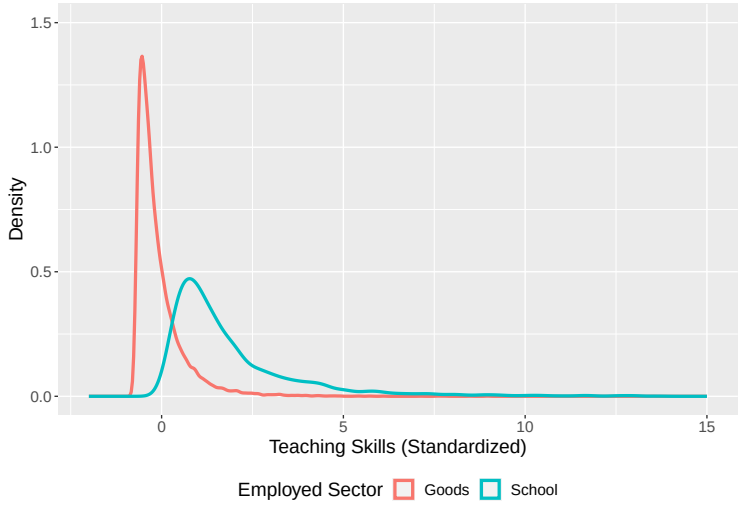
Variable	Description	Data Source	Methodology/Unit
$w_{i,m,E}$	Wage offer in the Educational sector for individual i in market m.	ACS-PUMS	Calculated from annual earnings for teachers, adjusted for contract length and hours worked per week (typically 10-month contracts).
$w_{i,m,NE}$	Wage offer in the Non-Educational sector for individual i in market m.	ACS-PUMS	Calculated from annual earnings for non-teaching occupations, adjusted as necessary.
$\delta_{0,E}$, $\delta_{0,H}$	Non-pecuniary utility parameters for Educational sector and Home production, respectively.	Estimated	Estimated using the structural model via Method of Simulated Moments.
Woman_i	Gender indicator; equals 1 if individual i is female.	ACS-PUMS	Derived from respondent's reported sex.
Ethnicity_i	Ethnicity indicators for individual i; includes categories such as White, Hispanic, African American, Asian, and Other.	ACS-PUMS	Derived from race and ethnicity variables.
Married_i	Marital status indicator; equals 1 if individual i is married.	ACS-PUMS	Based on marital status information.
Age_i	Age of individual i.	ACS-PUMS	Directly from respondent's age.

TABLE 14. Labor Supply Equation Variables

FIGURE 2. Teaching Skill Distribution for Markets 1 and 13 at Baseline



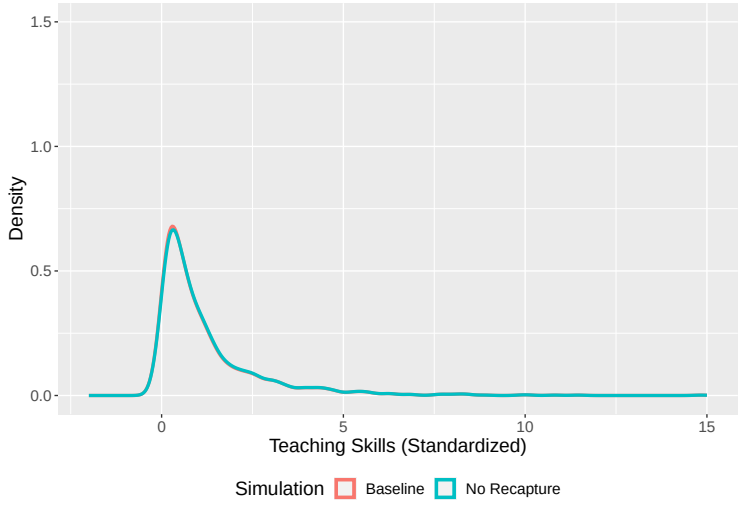
Market 1



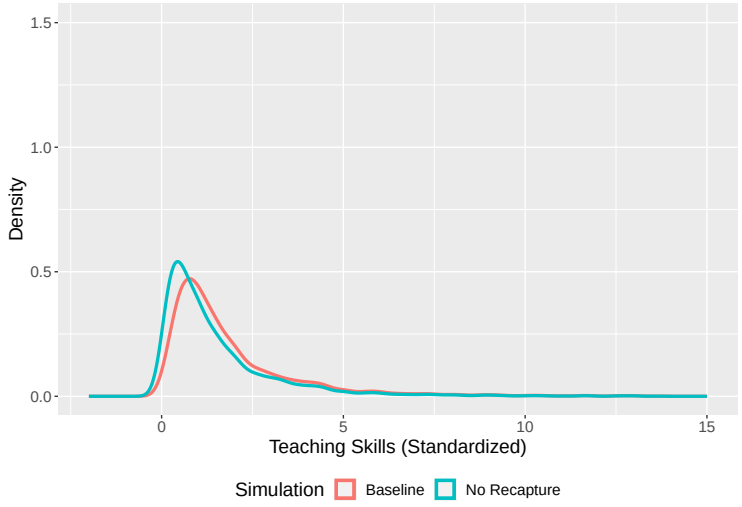
Market 13

Note: This figure shows teaching skill distribution of individuals employed in the Goods and Teaching sectors in Markets 1 and 13.

FIGURE 3. Teaching Skill Distribution of Teaching Sector - Baseline vs. Counterfactual



Market 1



Market 13

Note: This figure shows teaching skill distribution of individuals employed in the Teaching sectors in Markets 1 and 13 at baseline and under the counterfactual policy.

Wage Offers

The wage offers for individuals in both sectors are modeled as follows:

$$w_{i,m,E} = r_m \exp\left(X_i \lambda_E + \varepsilon_i^E\right),$$
$$w_{i,m,NE} = \exp\left(X_i \lambda_{NE} + \varepsilon_i^{NE}\right).$$

Variable	Description	Data Source	Methodology/Unit
$w_{i,m,E}$	Wage offer in the Educational sector for individual i in market m.	ACS-PUMS	Calculated from reported annual earnings for teachers, adjusted for contract length and hours worked per week.
$w_{i,m,NE}$	Wage offer in the Non-Educational sector for individual i in market m.	ACS-PUMS	Calculated from reported annual earnings for non-teaching occupations.
r_m	Skill rental price in the Educational sector in market m.	Estimated	Determined as part of the schools' optimization problem; estimated via the structural model.
X_i	Vector of observable characteristics for individual i, including education, experience, and demographic variables.	ACS-PUMS	Includes variables such as age, education level, gender, and ethnicity.
λ_E, λ_{NE}	Coefficient vectors for the wage equations in the Educational and Non-Educational sectors, respectively.	Estimated	Estimated through the structural model.

Continued on next page

TABLE 15 – *Continued from previous page*

Variable	Description	Data Source	Methodology/Unit
ε_i^E, ε_i^{NE}	Sector-specific random shocks affecting wage offers for individual i.	Assumed/Simulated	Modeled as random variables capturing unobserved factors; assumed to follow a certain distribution.

TABLE 16. Wage Offer Equation Variables

Educational Sector Production

The production function for the Educational sector is defined as:

$$\begin{aligned} \max_r \quad & \mathbb{E}[E_m] \\ \text{s.t.} \quad & E_m = \beta_0 + \beta_1 \ln S_m + X_m \beta + \xi_m \\ & F_m + T_m + P_m = W_m + C_m + R_m \end{aligned}$$

Variable	Description	Data Source	Methodology/Unit
E_m	Average student achievement in market m.	ERC	Measured by standardized test scores, such as STAAR exams in Math and English I, standardized to have mean zero and unit variance.
S_m	Aggregate teaching skills in market m.	Estimated	Sum of individual teacher skills in the market, estimated via the model from teacher characteristics and occupational choices.

Continued on next page

TABLE 17 – *Continued from previous page*

Variable	Description	Data Source	Methodology/Unit
X_m	Vector of student demographic variables in market m.	ERC	Includes proportions of female students, race/ethnicity distributions, economic disadvantage status, ESL status, etc.
β_0, β_1, β	Parameters of the achievement function.	Estimated	Estimated via the structural model using student achievement data.
ξ_m	Error term in the achievement function for market m.	Assumed	Captures unobserved factors affecting achievement; assumed to have mean zero.
F_m	Federal funding received by schools in market m.	PEIMS Financial Data	Total federal revenue for the market, divided by number of students; measured in dollars per student.
T_m	State transfers to schools in market m.	PEIMS Financial Data	Total state revenue for the market, including recapture funds received, divided by number of students; measured in dollars per student.
P_m	Local property tax revenue in market m.	PEIMS Financial Data	Total local revenue from property taxes, net of recapture payments, divided by number of students; measured in dollars per student.

Continued on next page

TABLE 17 – *Continued from previous page*

Variable	Description	Data Source	Methodology/Unit
W_m	Total wages paid to teachers in market m.	PEIMS Financial Data	Total instructional payroll expenses, divided by number of students; measured in dollars per student.
C_m	Other educational expenditures in market m, such as materials and services.	PEIMS Financial Data	Sum of non-payroll operational expenditures, divided by number of students; measured in dollars per student.
R_m	Recapture payments made by schools in market m to the state; may be positive or zero.	PEIMS Financial Data	Total recapture payments made, divided by number of students; measured in dollars per student.

TABLE 18. Educational Production Function Variables

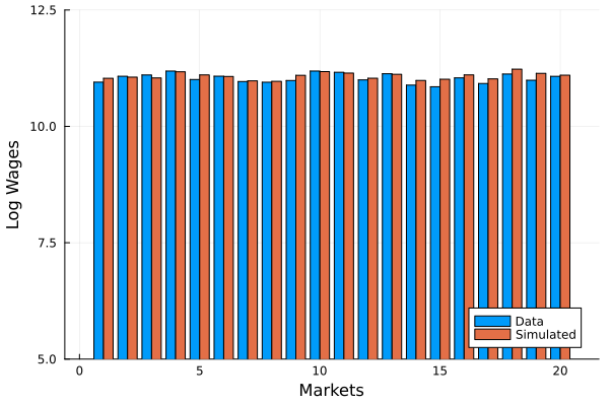
Appendix B. Model Fit

This appendix presents the model fit results for the labor supply decisions and educational sector outcomes. By comparing simulated data generated from our estimated model with actual observed data, we assess the model's performance in capturing key patterns in occupational choices, wage distributions, and student achievement across different markets.

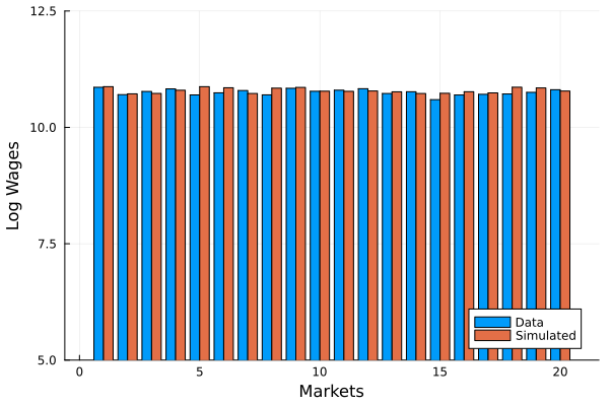
Figures 4 to **??** display comparisons between the simulated and actual data for the labor supply model. Figure 4 shows the wage distributions for both the non-educational (Others) and teaching sectors across the 20 markets. The simulated wage distributions closely align with the actual data, indicating that the model effectively captures wage structures in both sectors. It accurately reflects the higher variance in wages within the non-educational sector compared to the teaching sector, as well as the differences in wage levels across markets.

Figure 5 illustrate the occupational choice frequencies among the three options: working in the non-educational sector, working as a teacher, or staying at home. The simulated occupational choice proportions match the actual data remarkably well across all markets.

FIGURE 4. Model Fit - Log-Wages



Other Sectors



Teaching Sector

Note: This figure shows the simulated average log-wages in each of the 20 markets, compared to the actual data points.

Figure 6 compares the simulated average student achievement scores with the actual data across the 20 markets. The model-generated achievement scores closely follow the observed data, demonstrating the model's ability to capture the relationship between aggregate teacher skills, student characteristics, and educational outcomes.

Overall, the model demonstrates strong fit with the actual data in both the labor supply and educational sectors. The close alignment between the simulated and observed wage distributions, occupational choices, and student achievement scores suggests that the estimated parameters capture the essential determinants of individual decisions and market outcomes. The model's ability to account for regional variations is particularly noteworthy. By incorporating market-specific parameters, such as wage constants and skill rental prices, the model reflects the diverse economic conditions and labor market dynamics across different regions. This feature enhances the model's explanatory power

and its applicability to policy analysis targeting specific markets.

The successful model fit provides confidence in using the estimated parameters for further analyses, such as counterfactual simulations or policy evaluations. By accurately representing the underlying mechanisms driving labor supply decisions and educational outcomes, the model serves as a robust tool for exploring the potential impacts of changes in wages, education policies, or demographic shifts.

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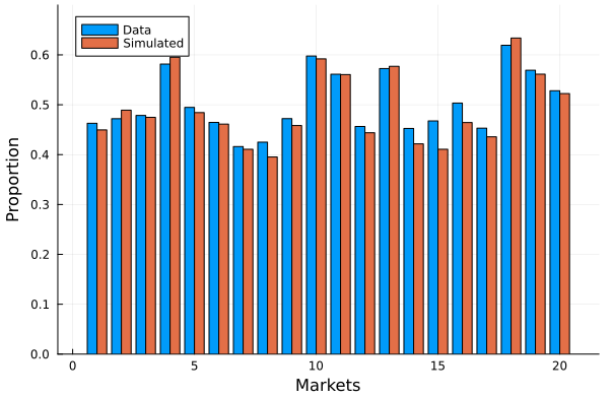
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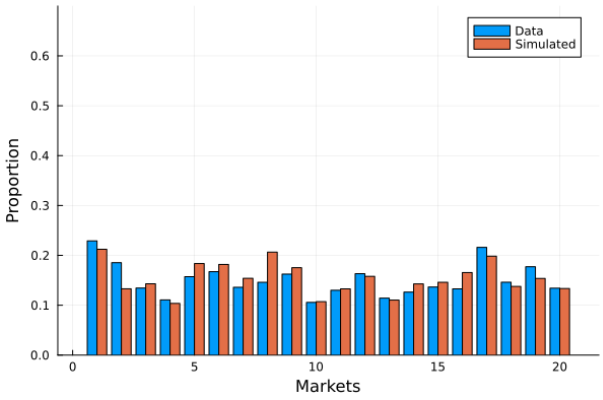
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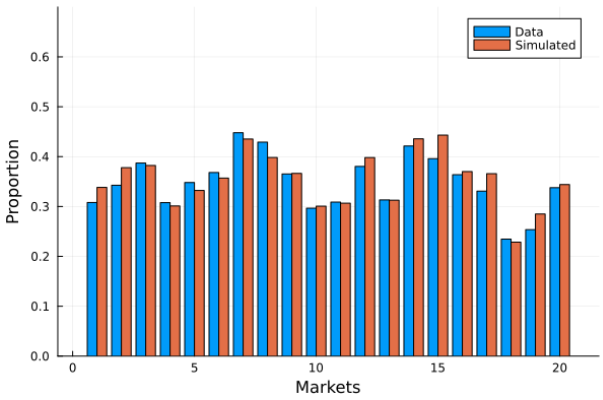
FIGURE 5. Model Fit - Choice Frequencies



Other Sectors



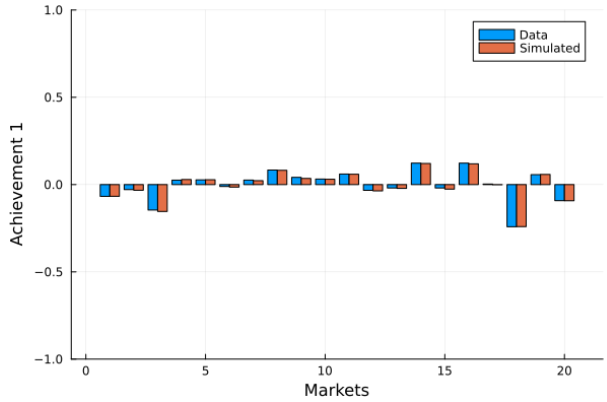
Teaching Sector



Home

Note: This figure shows the simulated average choice frequencies in each of the 20 markets, compared to the actual data points.

FIGURE 6. Model Fit - Test Scores



Note: This figure shows the simulated average test scores in each of the 20 markets, compared to the actual data points.