The Population Aging Effect on Local Productivity and Costs: Evidence from Thailand*

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Abstract

Population aging is reshaping economies worldwide, yet evidence on its local effects in developing countries remains scarce. This paper exploits spatially uneven aging across Thailand — a middle-income economy undergoing rapid demographic transition — to identify the causal impacts of aging on local economic outcomes. Combining geo-referenced labor force and household consumption surveys, population registers, and administrative data, we find that a one-percentage-point increase in the sub-district elderly share raises local wage premiums by 2.7 percent and rental costs by 2.6 percent, while reducing household rental expenditure shares by 0.6 percentage points. Firm censuses corroborate these patterns, particularly in manufacturing, where the same increase in aging raises establishment-level revenue per man-hour by 3.8 percent annually and concentrates workers in larger units. These results are consistent with theories in which aging leads to greater regional consumption and capital accumulation per capita, and sustains agglomerations due to the presence of capital mobility frictions. Subnational

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data on savings and loans are suggestive of this mechanism: aging-induced savings appear to raise local investment, underpinning the observed gains in worker productivity and firm performance.

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1 Introduction

Two-thirds of the world's population now lives in countries where the birth rate has fallen below the replacement level needed to sustain population sizes. When national fertility rate falls approximately below 2, absent net migration, population over the long-term is expected to shrink. The fertility rate for most countries that have hit this threshold – including Europe, Australia, Japan in 1970 and China, India and United States more recently — has not experienced a rebound since, meaning that low fertility rate and rapid aging is likely going to be a persistent global future trend (Geruso and Spears, 2026).

The economic implications of these demographic trends are under active scholarly debate. The existing literature has emphasized the negative effects of population aging on a range of outcomes including GDP growth (Gagnon et al., 2021; Fernandez-Villaverde, 2025), aggregate consumption (Sheiner, 2014), knowledge creation and living standards (Jones, 2022), total factor productivity (Aiyar et al., 2017), and fiscal sustainability (Sheiner, 2021). A more optimistic view is offered by Weil (2026), who finds that the effect of sub-replacement fertility on US consumption is negative but small, approximately 8.7 percent spread over multiple decades. A separate strand of the literature emphasizes endogenous adjustments that can mitigate the economic costs of aging. Vogel et al. (2017) show that labor scarcity in aging European economies has induced endogenous improvements in human capital that has partially offset the effects of a shrinking workforce. Acemoglu and Restrepo (2017) find no systematic negative relationship between aging and GDP per capita growth across countries between 1990 and 2015, attributing this to the adoption of labor-saving robotic technologies in response to demographic pressure. Maestas and Zissimopoulos (2010) argue that aging populations adjust by delaying retirement and transitioning toward cognitively intensive occupations, alleviating the burden of rising dependency in the United States. More recently Acemoglu et al. (2026) finds that areas with historically lower birth rates are associated with higher growth in GDP per working-age adult across countries and higher wage growth across US commuting zones, with no negative impact on aggregate

GDP or earnings.

Much of this literature has focused on aggregate national or cross-country outcomes in high-income settings, leaving open the question of how aging shapes the geographic distribution of economic activity *within* developing countries. Evidence from economic geography points to considerable spatial misallocation of factors in such settings, reflecting frictions in trade and factor mobility (Bryan et al., 2014; Bryan et al., 2015). As such, the returns to density are substantially larger in developing economies than in rich ones: doubling population density is associated with a wage premium of roughly 4 percent in high-income countries (Ahlfeldt and Pietrostefani, 2019), compared with 19 percent in China and 12 percent in India (Chauvin et al., 2017; Grover et al., 2023). These earnings premia reflect underlying differences in labor productivity across locations (Roback, 1982), which reinforce concentration until the costs of agglomeration—higher housing prices (Moretti, 2013), congestion (Glaeser and Kahn, 2004), crime (Glaeser, Sacerdote, and Scheinkman, 1996), and pollution (Chay and Greenstone, 2005)—offset the gains from incremental density (Moretti, 2004; Diamond, 2016).[1]

Differential aging patterns *within* countries can further shape economic geography. The empirical literature on aging has focused primarily on the adverse consequences of a shrinking working-age population. If aging operates mainly through this labor-supply channel, the thinning of local working-age pools should weaken agglomeration and push activity away from aging regions. Aging, however, also raises local demand for goods and services and lifts regional savings rates. Under the factor mobility frictions typical of developing countries, the additional demand and savings can raise local investment, attract firms, and deepen agglomeration, yielding higher productivity premia alongside higher urban costs. In higher-income countries, internal factor mobility faces fewer frictions, so the effects of aging likely operate mainly through the adverse labor-supply channel. In developing countries, by contrast, which channel dominates remains an open empirical question. At the cross-country level, Pritchett (2026) emphasizes the scope for labor reallocation from high-fertility, low-productivity developing countries to low-fertility, high-productivity high-income ones in response to rapid aging among the latter. An analogous within-country reallocation is plausible: where aging raises local productivity, enabling workers to move to aging, high-productivity regions can correct spatial misallocation and raise aggregate output (Hsieh and Moretti, 2019).

This paper is set in Thailand — a middle-income economy undergoing rapid demographic transitions in Southeast Asia. Thailand's total fertility rate fell below replacement level in 1991 and has continued to decline without reversal (World Development

[1] An alternative explanation for productivity premia is selective sorting of workers across locations, which we address explicitly below.

Indicators, 1978). The elderly population share is projected to rise from 13% in 2020 to 31% by 2060 (Moroz et al., 2021). In 2004, only 17 of Thailand's approximately 7400 sub-districts — known as tambons[2] — had elderly shares exceeding 15 percent; by 2019, this had risen to over one thousand, while tambons with very low elderly shares nearly disappeared. These changes have been spatially uneven, with central regions aging more rapidly than other areas.

Existing literature shows strong savings behavior among elderly populations in Thailand. Using data from the Thailand Household Socio-Economic Survey (HSES), Rochanahastin and Horayangkura (2025) show a hump-shaped life-cycle pattern in saving behavior, with household savings — calculated as the difference in total household monthly income and expenses —peaking among heads between the ages of 56 and 65.

Thailand also exhibits pronounced geographic disparities in earnings. In 2020, average incomes in Bangkok were nearly twice those in the Central region and more than 6.5 times higher than in the Northeast (Belghith et al., 2023). The Bangkok metropolitan area has a population 29 times larger than Chiang Mai and a GDP 40 times greater than Chon Buri, the country's third-largest economic center (World Bank, 2024). The combination of rapid, spatially uneven demographic change and large earnings disparities makes Thailand a compelling context for studying the local agglomeration effects of aging — and examine the potential channels of labor scarcity, localized demand shocks and the role of savings and investment — in a developing country.

Our empirical work combines two theoretical building blocks. Grafeneder-Weissteiner and Prettner (2013) embed an overlapping generations structure in a spatial setting: because older cohorts hold more wealth and consume more per capita than newborns, aging regions accumulate capital faster and generate higher local expenditure[3]. This expenditure shift raises capital rental rates and attracts firm activity, triggering Baldwin's (1999) demand-linked circular causality — but only if capital is imperfectly mobile, since frictionless mobility would channel the aging-induced accumulated capital/savings to higher-return regions and decouple local demand from local production. There is documented evidence of capital mobility frictions in developing countries, particularly in China (Boyreau-Debray and Wei, 2004). Under such frictions, aging acts as an agglomerative force, concentrating workers, firms, and production in rapidly aging locations and generating wage premiums as well as higher local costs.[4]

[2]Thailand is administratively divided into 77 provinces (changwat), 878 districts (amphoe), and approximately 7,700 sub-districts (tambons), each typically containing between 5 and 20 villages (mubans).

[3]Weil (2026) shows that in the United States, consumption among those over 60 can exceed 1.5 times that of working-age adults, compared to 0.5 times for children under 5.

[4]Alternate spatial models studying the agglomeration effect of aging reach similar conclusions (Gaigné and Thisse, 2009; Naito and Omori, 2017; Takahashi, 2022).

To test these predictions, we use Thailand's quarterly Labor Force Survey (LFS) from 2004 to 2011, which tracks individuals continuously over six quarters. The panel structure allows us to separate individual-level observed and unobserved fixed effects from location-specific productivity. We complement the LFS with area-level rental costs and rental expenditure shares from the annual Socio-Economic Survey (2006–2019) and with establishment-level outcomes from the 2012, 2017, and 2022 firm censuses, all georeferenced to the tambon. These are merged with annual population registers from Thailand's Department of Provincial Administration (DOPA), available from 1998 and provide spatially disaggregated demographic records at a resolution rarely available in developing countries.

The main empirical challenge is that unobserved local shocks jointly drive demographic structure and economic outcomes: an adverse shock that induces out-migration of working-age residents mechanically raises the elderly share, imparting downward bias on OLS estimates. We address this with a Bartik-style shift-share instrument developed in Maestas et al. (2023) that interacts tambon-level age-cohort shares from 1998 with Thailand's national cohort survival rates over 2004–2019 to construct predicted elderly shares. The instrument isolates aging driven by the pre-determined age structure rather than by contemporaneous economic conditions. The identifying assumption is that the 1998 age distribution affects subsequent changes in local economic outcomes only through its effect on changes in the elderly share. We examine the validity of this assumption through several robustness checks and diagnostics tests outlined in Goldsmith-Pinkham, Sorkin, and Swift (2020).

Our findings are as follows. The main motivating finding is that a one-percentage-point increase in the local elderly share raises the productivity premium by 2.7 percent and average rental prices by 2.6 percent, while lowering the household rental expenditure share by 0.6 percentage points. These estimates are robust to alternative specifications, instruments, estimators, outlier-detection procedures, alternative definitions of the elderly population, and controls for changes in other segments of the age distribution. We find limited evidence that labor scarcity accounts for the wage and rental premia. Instead, we find that aging raises local demand, incomes and savings, and under frictions to capital mobility, this leads into higher local investment. We use district-level administrative data on commercial bank deposits and loans, apply an IV mediation analysis based on Dippel, Gold, Heblich, and Pinto (2022) to study the role of aging, savings and local investment. A one-percentage-point rise in the district-level elderly share—which takes roughly five years—raises local savings by 11.5 million baht, and each additional baht of local savings translates into 0.85 baht of local investment, accounting for the bulk of aging's total effect on investment. The direct effect of aging

on investment, net of the savings channel, is negative. Firm-side outcomes reinforce these results. In tradable and capita-intensive manufacturing sector, the same rise in the elderly share raises tambon-level revenue per man-hour by 3.8 percent annually, alongside higher wage bills, higher investment rates, and greater concentration of workers within establishments—with no change in the aggregate number of manufacturing workers within sub-districts. This pattern is consistent with agglomeration-driven productivity gains. Non-tradable and less capital intensive services move in the opposite direction: revenue per man-hour falls by 1.4 percent annually, accompanied by declines in employment and the wage bill, and no detectable agglomeration response.

To our knowledge, this paper provides the first causal estimates of aging's effect on local productivity and costs within a developing economy, contributing to several strands of literature.

First, we add to the growing body of work showing that endogenous adjustments can mitigate the consequences of persistent sub-replacement fertility. In our setting, agglomeration-driven productivity gains emerge as one such margin, complementing previously studied adjustments including international migration (Pritchett, 2026), greater use of robotics (Acemoglu and Restrepo, 2017), human capital deepening (Vogel et al., 2017), and delayed retirement (Maestas and Zissimopoulos, 2010). Our results point to capital deepening as a response to aging, arising from frictions to internal capital mobility, commonly observed in developing countries. The mechanism differs from the one Acemoglu et al. 2026 identify in high-income economies, where deepening follows from firm investment in labor-saving robotic technologies, but the implication is similar: aging induces adjustments on the capital margin that offset part of its effect on labor supply.

Second, we contribute to the urban economics literature by identifying age composition as a force shaping agglomeration. Most existing work on the economic effects of aging operates at the national or cross-country level, and the few studies examining subnational consequences reach mixed conclusions. Maestas, Mullen, and Powell (2023) find that aging reduced U.S. state-level GDP-per-capita growth by 0.3 percentage points annually between 1980 and 2010, two-thirds of this effect operates through slower labor productivity growth. Giannone et al. (2023) document that rural youth out-migration in Japan produced endogenous amenity decline and dispersion of activity in aging areas. Takahashi (2022), by contrast, shows that Japan's elderly are *more* concentrated in large agglomerations than younger cohorts. These studies focus on different margins (growth, youth migration, elderly location choices) and on high-income settings. Our contribution is to identify a distinct mechanism — capital deepening through the savings channel — operating in a developing economy where factor mobility frictions

amplify its spatial impact.

The remainder of the paper is organized as follows. Section 2 describes our main data sources. Section 3 provides a theoretical framework for the effects of demographic aging on local economic outcomes. Section 4 presents the research design, Section 5 estimates of wage and rental premia due to aging, Section 6 examines the role of labor supply contractions, Section 7 examines the role of pure-demand shocks associated with aging, Section 8 presents the role of savings and investment in the presence of capital mobility frictions. Section 9 examines firm-level outcomes, and Section 10 concludes.

2 Data

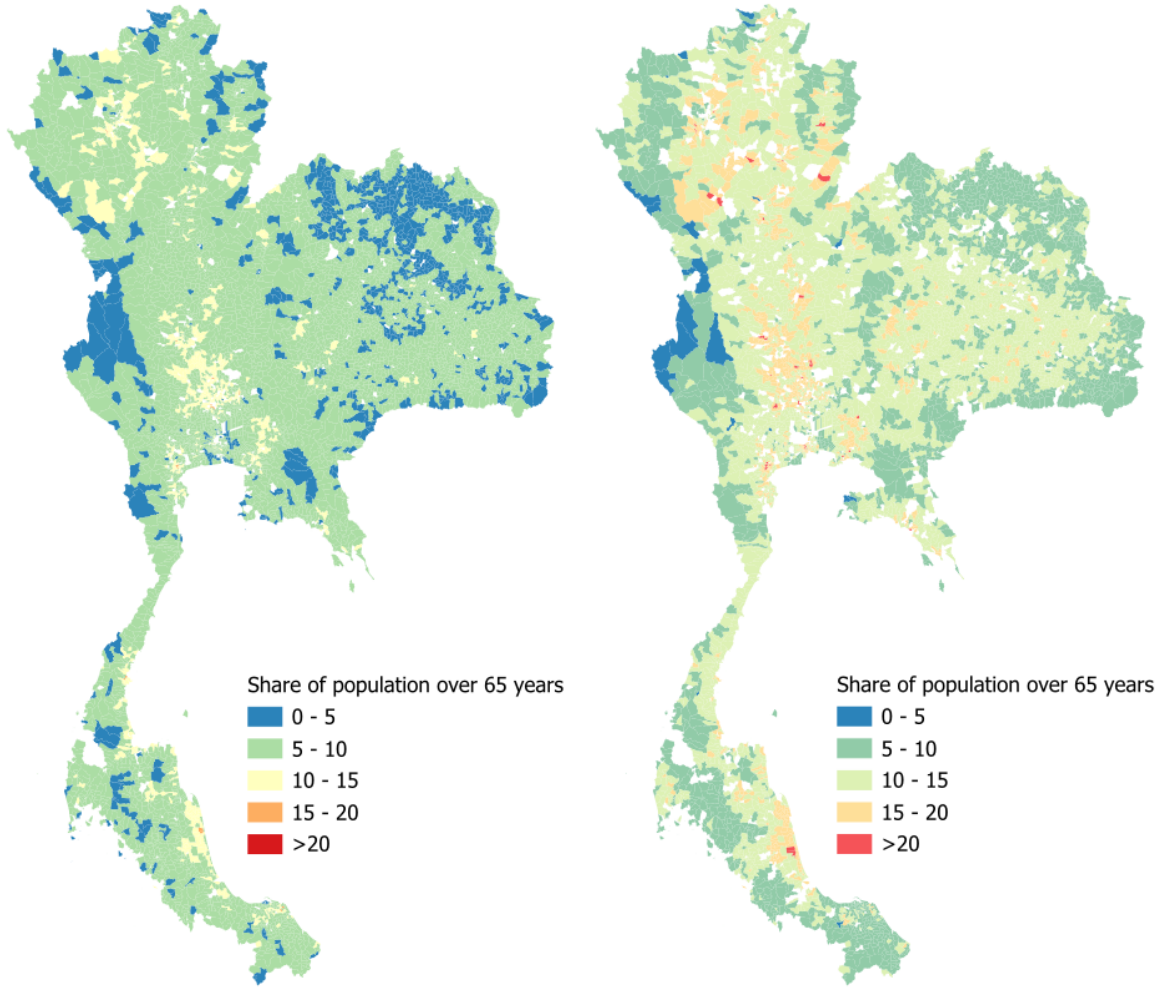
2.1 Population Statistics

Demographic data, disaggregated by gender and single-year age groups up to age 101 at the tambon level, come from population registers maintained by the Registration Administration Bureau under Thailand's Department of Provincial Administration (DOPA). The series begins in 1998 and includes counts of non-Thai residents and annual estimates of Thai migrants by tambon-year.[5] We georeference the registers using tambon-level administrative shapefiles from Thailand's Geo-Informatics and Space Technology Development Agency (GISTDA) and exclude tambons with fewer than 500 residents in any year. Thailand contains approximately 7,400 tambons, with a mean area of 69.4 km^2; we further exclude tambons below 0.97 km^2 or above 428.5 km^2, corresponding to the 1st and 99th percentiles of the size distribution. Average tambon population density was 391 persons per km^2 in 2004 and declined slightly to 388 persons per km^2 by 2019.

Figure 1 maps the spatial distribution of the elderly population share (aged 65 and above) across tambons in 2004 and 2019. In 2004, only 17 tambons had an elderly share above 15 percent; by 2019, 1,040 tambons crossed this threshold. Over the same period, the number of tambons with an elderly share below 5 percent fell from 810 to 25. The map reveals substantial spatial heterogeneity in the pace of aging, which we exploit in the below empirical sections.

Figure 2 plots tambon-level annual changes in the number of children under age 1 as well as annual changes in the elderly population. The youngest cohort contracts progressively over time, reaching a 5 percent decline by 2022, while the elderly population grows at a stable rate of just under 5 percent per year throughout the period. Together, these patterns reflect both declining mortality among older cohorts and sharply falling

[5] https://stat.bora.dopa.go.th/stat/statnew/statMenu/newStat/home.php



(a) 2004 (b) 2019

Figure 1: Share of population over 65 year in 2004 and 2019
Source: DOPA

fertility. The transition has also been spatially uneven: as shown in Appendix Figure A1, provincial elderly shares across Bangkok, its adjoining provinces, and the rest of the country were broadly comparable at the start of the millennium, but by 2022 Bangkok's elderly share exceeds 15 percent—roughly three percentage points above the national average and four points above the surrounding Bangkok Metropolitan Region provinces.

Appendix Figure A2 plots ten-year growth in real gross provincial product (GPP) per capita between 2004 and 2020 against the change in the elderly population share at the provincial level over the same period. The figure reveals a positive cross-sectional association between the pace of aging and provincial output growth, a relationship that persists when the Bangkok Metropolitan Area is excluded from the sample.

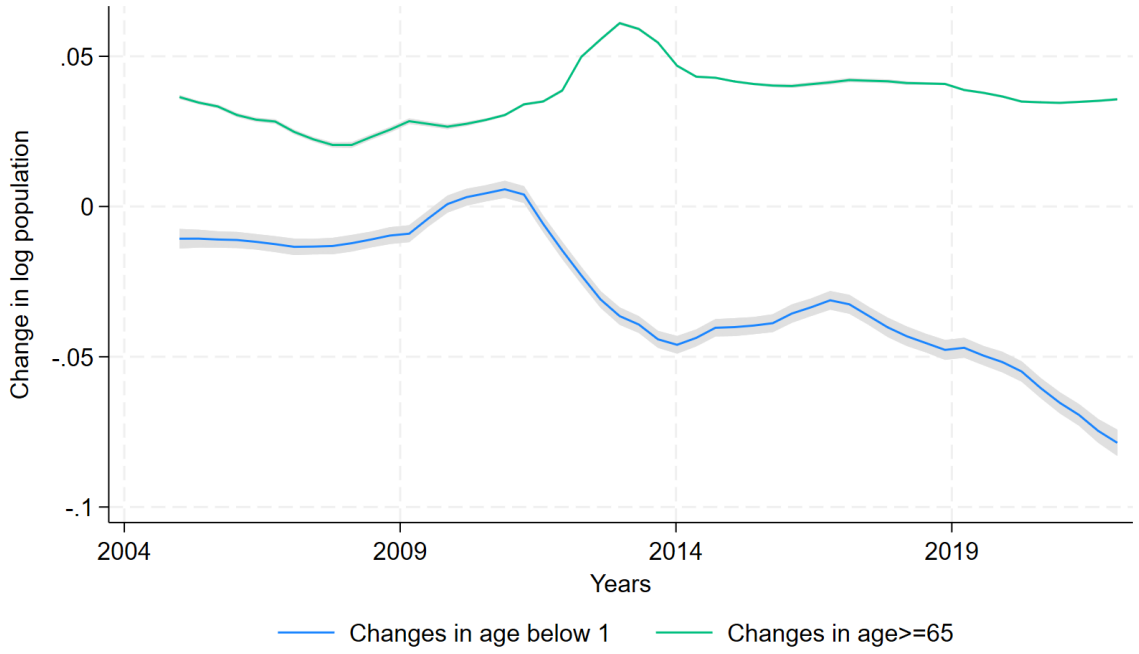


Figure 2: Annual change in log population at the tambon level: children under 1 and elderly aged 65 and above
Source: DOPA. The vertical axis is the difference in log population across consecutive years for each age group.

2.2 Wages

We use wage data from Thailand's quarterly Labor Force Survey (LFS), administered by the Thailand National Statistical Office (TNSO). Each round covers roughly 220,000 households and includes geographic identifiers at the province (changwat), district (amphoe), and tambon levels. We obtained access to these identifiers for all quarterly rounds between 2004 and 2019, and use them to georeference survey observations with GISTDA shapefiles and link them to DOPA's population registers.

The LFS employs a rotating panel structure that follows households over two years using a "2-2-2" design: each household is surveyed for two consecutive quarters, rotates out for two quarters, and returns for two final quarters. The first set of rotation panels remained in the field from 2004 to 2011; a full sample refresh in 2011 introduced a new cohort of households, surveyed over the following decade under the same design. Consistent household identifiers across rounds allow straightforward deterministic matching of households over time. Linking individuals within a household across rounds is more difficult, however, because person-level identifiers within a household are not recorded consistently.

To address this challenge, we develop a conservative deterministic matching algo-

rithm that tracks individual workers across survey rounds, detailed in Appendix B.1. This yields a worker-level panel spanning 2004–2019[6]. The approach minimizes errors in individual-level mismatches across rounds and recovers approximately 50 percent of individuals in the raw LFS data.

Finally, because wage information is recorded only for wage and salaried workers, self-employed individuals, unpaid family workers, and others are excluded from the panel. Salaried workers returning zero wages — roughly 1% of the salaried group —are also excluded. Since we use wage data to construct tambon-level labor productivity measures based on observed earnings, we follow Moretti (2004) and retain wages denominated in nominal Thai Bahts.

Summary statistics for the worker panel are reported in Appendix Table A1. The sample covers more than 3,000 tambons and between 400,000 and 700,000 wage earners per period. Key demographic indicators are reassuringly stable across periods (given the longitudinal nature): the average worker is 36 to 38 years old, lives in a household of roughly three members, and is slightly more likely to reside in an urban area. The sample has higher representation from the Central region, with above-secondary education levels and employment concentrated in non-farm sectors — consistent with the fact that wage and salaried workers tend to be more educated and employed outside agriculture. Average weekly hours worked are stable at approximately 45 across the three periods, and nominal daily wages exhibit a rising trend, with the sharpest increase occurring in the final four years of the sample period (2015-2019).

Appendix Figure A3 plots decadal changes in gross provincial product per worker manhour, mean log wages, and elderly population shares over 10-year intervals spanning 2004–2019, separately for manufacturing and services. Three patterns are visible. First, decadal wage growth in both sectors tracks the trends in national accounts data closely, providing external validation of the labor force survey-based wage estimates. Second, provinces experiencing faster aging show relatively higher growth in output per manhours and wages. Third, the positive relationship between aging and both wage and output growth is more pronounced in manufacturing than in services.

2.3 Rental Costs

We obtain monthly rental costs from the annual Socio-Economic Survey (SES), also administered by TNSO. The rental variable captures both actual rents paid by tenant

[6]Samart et al. (2021) and Hawley et al. (2024) adopt similar approaches to exploit the panel structure of the Thai LFS. Their methods use fuzzy matching algorithms designed to maximize panel size at the cost of some imprecision in linking individuals across rounds. Our algorithm, by contrast, matches workers using observed characteristics under unambiguous deterministic criteria, producing a smaller panel but minimizing false matches.

households and imputed rental values reported by owner-occupier households, measured both in levels and as a share of total household consumption expenditure. We also draw on a broader set of housing and household characteristics from the SES, including household size, dwelling type, construction materials, tenure status, whether the unit hosts a business, number of rooms and bedrooms, access to electricity, cooking fuel, drinking water source, water supply type, garbage disposal method, toilet facility, and whether the household resides in a municipality.

As with the LFS, we were granted access to tambon-level geographic identifiers for the SES covering 2006 to 2019, which we use to georeference observations and link them to DOPA population registers. Unlike the LFS, however, the SES is a repeated cross-section rather than a panel. Appendix Table A2 shows a steady rise in nominal rents over the sample period, though the share of rent in total household expenditure has remained relatively stable. The typical dwelling in the sample is a detached, owner-occupied unit with roughly three rooms, two of which are bedrooms, and near-universal access to electricity.

2.4 Firms

We obtain establishment-level data from Thailand's manufacturing censuses for 2012, 2017, and 2022 and services censuses for 2012 and 2022. Both censuses enumerate all establishments with at least ten workers and draw a random sample of smaller establishments. Industry codes follow the five-digit Thai Standard Industrial Classification (TSIC), and the manufacturing census further disaggregates output by up to four products per establishment under the Classification of Production by Activities (CPA). For each establishment, we use annual revenues, the book value of capital assets[7], marketing and transportation costs,[8] and total workers, aggregating these to the tambon-year level. We then georeference and link the data to the population registers as before. Summary statistics in Appendix Table A3 show that average nominal revenue and capital grew faster in manufacturing than in services between 2012 and 2022, while the number of firms per tambon declined more sharply in manufacturing and average employment rose more in services.

[7]Capital assets include land, buildings and construction, machinery, vehicles, office appliances, equipment, and other fixed assets held by the establishment at the end of the calendar year.

[8]These include advertising, transportation, commissions, electricity and water, accounting and consulting, entertainment, waste disposal, security, gardening, fuel for transportation, postage, telephone, stationery, insurance, research and development, rental of vehicles, equipment, and buildings, interest payments, bad debt charges, training, and foreign exchange losses.

2.5 Other datasets

For our robustness checks, we supplement these four main datasets—covering population, wages, rentals, and firm-level outcomes—with data on local amenities from OpenStreetMap (OSM), including tambon-level counts of health facilities, retail outlets, food and beverage establishments, hotels, and transport hubs as of 2025. We also use harmonized annual nighttime lights data from Li et al. (2020), which span 1992–2024 at 30 arc-second spatial resolution and reconcile the incompatible DMSP-OLS (1992–2013) and VIIRS-DNB (2012–present) series. In additional robustness exercises, we draw on district-representative microdata from Thailand's 1990 population census, obtained through IPUMS, to verify that our main results based on population registers are consistent with an independent demographic source.

Finally, to examine the channels through which aging affects local savings and investment, we use district-level monthly data on total loans and deposits from the Bank of Thailand between 2005 and 2022. The data cover banks registered in Thailand and branches of foreign banks. Deposits include all types of deposits from households, firms, and other financial institutions, as well as negotiable certificates of deposit (NCDs) issued to the public. Loans cover commercial bank lending including overdrafts; the purchase, discount, and rediscount of bills of exchange (B/E); and advance payments on all guaranties.

3 Theoretical Predictions

Our first building block is Baldwin (1999), which formalizes agglomeration in a two-region economy where firms prefer proximity to larger markets. A positive income shock in region H raises profits and capital rental rates, expanding local incomes and expenditure. The resulting demand shift induces further firm activity, amplifying the initial shock through demand-linked circular causality. Critically, these agglomeration forces sustain only under frictions to capital mobility. With frictionless capital markets, higher incomes in H would flow freely to the other region, decoupling expenditure from production and breaking the circular causality mechanism. Mobility frictions close this loop: by tying production to the locations where income and expenditure are rising, they sustain demand-linked agglomeration.

Our second building block, Grafeneder-Weissteiner and Prettner (2013), supplies a demographic source for these income shocks. In their model, at each instant a fraction μ of the elderly die and are replaced by a measure β of newborns who enter with zero wealth, so that population growth is $n = \beta - \mu$. Because older individuals hold accu-

mulated capital and consume more than the newly born, generational turnover governs aggregate per-capita expenditure at the local level. The aggregate Euler equation is

$$\frac{\dot{\tilde{c}}(t)}{\tilde{c}(t)} = \frac{\dot{c}(t_0,t)}{c(t_0,t)} - \beta\frac{\tilde{c}(t) - c(t,t)}{\tilde{c}(t)}, \tag{1}$$

where $c(t,t)$ is the consumption of a newborn at birth, $\tilde{c}(t)$ denotes aggregate per-capita consumption, and tildes denote per-capita normalization $\tilde{X}(t) \equiv X(t)e^{-nt}$. The second term captures the generational turnover drag: replacing high-consuming elderly with low-consuming newborns depresses aggregate per-capita consumption growth. The law of motion for per-capita capital is

$$\dot{\tilde{k}}(t) = \frac{\tilde{l}}{a_i} - \frac{\tilde{c}}{w(t)a_i} + \left(\frac{\pi(t)}{w(t)a_i} - \delta - \beta + \mu\right)\tilde{k}(t), \tag{2}$$

where $\tilde{l}$ is per-capita labor in efficiency units, $w(t)$ is the efficiency wage, $\pi(t)$ is the capital rental rate, a_i is the unit labor input coefficient, and δ is the depreciation rate.

Three demographic scenarios clarify the distinct roles of population growth and generational turnover. Pure population growth without turnover ($\beta > 0$, $\mu = 0$, $n > 0$) dilutes per-capita capital accumulation through equation (2), weakening local demand. Pure turnover without population growth ($n = 0$, $\beta = \mu > 0$) depresses per-capita consumption through equation (1), since newborns consume less than the population average, attenuating the circular demand channel. Rapid aging ($\beta \ll \mu$, $n < 0$) reverses both forces simultaneously: the sharp decline in birth rates shrinks the generational turnover drag while population decline raises the coefficient on $\tilde{k}(t)$ in equation (2) through the $-\beta + \mu$ term, accelerating per-capita capital accumulation. The resulting expansion in local expenditure and accumulated capital strengthens demand for firms in H. This rapid-aging scenario corresponds closely to Thailand's current demographic trajectory — see Figure 2 — birth rate lags mortality leading to a decline in population growth n.

The two building blocks can be combined. Aging generates the demand and capital accumulation, but whether these translate into agglomeration through Baldwin(1999) depends on capital mobility frictions. Under frictionless capital markets, aging-induced savings flow to wherever returns are highest, bearing no systematic relationship to local investment and severing the link between demographic change and spatial production patterns. Mobility frictions preserve this link: by keeping savings local, they allow aging-induced capital accumulation to raise local investment and activate agglomeration forces.

Evidence of such frictions at the cross-country level is obtained by regressing na-

tional investment rates on savings rates, interpreting a positive coefficient as evidence of frictions, since under frictionless mobility savings would flow to the highest-return investment opportunities worldwide and the coefficient would be zero. Feldstein and Horioka (1980) report a cross-country coefficient of 0.72 for 1960–1974, well above the frictionless benchmark of zero. Subsequent estimates confirm the pattern: Obstfeld and Rogoff (2000) find 0.60 for 1990–1997, and Eaton, Kortum, and Neiman (2016) report 0.25 for 2001–2008 and 0.63 for 2009–2012. Appendix Table A4 replicates this exercise *within* Thailand using district-level savings and loans data from the Bank of Thailand over 2005–2022. Regressing per capita loans on per capita savings, in both levels and ten-year long differences, we obtain coefficients between 0.513 and 0.582, rising further when Bangkok is excluded. This is suggestive of capital mobility frictions within Thailand.

Together, these building blocks identify the causal chain linking aging to agglomeration. First, population aging raises per-capita consumption and capital accumulation in affected regions, as established by Grafeneder-Weissteiner and Prettner (2013). Second, under capital mobility frictions of the kind documented by Feldstein and Horioka (1980) and replicated here for Thailand, aging-induced savings raise local investment rather than dispersing to higher-return locations. Third, consumption and capital accumulation in the presence of mobility frictions trigger the demand-linked circular causality of Baldwin (1999), concentrating economic activity in aging regions. The testable prediction follows: tambons experiencing larger increases in elderly share, controlling for changes in total population growth (or population density growth), should exhibit higher wage premiums, higher rental costs, greater investment and capital stock, and greater concentration of productive activity, with the investment response operating through the savings channel.

4 Research Design

In this section, we first outline our method to recover wage and cost premiums from survey data in section 4.1, then specify our estimating equation in section 4.2 and introduce our instrumental variable in section 4.3.

4.1 Estimating Area-level Wage Premiums and Rental Costs from Surveys

Following Combes and Gobillon (2015), we model log monthly wage of a worker i, residing in tambon c and employed in industry $s(i,t)$ at time t, as:

$$\log y_{it} = u_i + X_{i,t}\theta + Z_{c,t} + \eta_{c,s(i,t),t} + \epsilon_{i,t} \tag{3}$$

where u_i is a worker fixed effect, $X_{i,t}$ is a vector of time-varying worker characteristics (age, age-squared, and occupation based on ISCO codes, with age variables mean-centered at the industry–year level) and $\eta_{c,s(i,t),t}$ denotes industry–location interactions.

The term $Z_{c,t}$ captures tambon-level wage premium, after controlling for worker characteristics and location–industry–specific factors. In standard Roback (1982) models, differences in location-specific wages, $Z_{c,t}$, reflect differences in local productivity.

A key challenge in recovering unbiased estimates of $Z_{c,t}$ is accounting for unobserved worker heterogeneity—such as ability, risk preferences, or access to financial and political networks—that may drive the endogenous sorting of workers across locations, biasing the estimates of tambon-specific wages upward. Accounting for these unobserved characteristics requires worker-level panel data, which is generally unavailable in developing-country settings. Prior studies in Colombia (Duranton, 2016), India, China, and Brazil (Chauvin et al., 2017) estimate similar specifications to recover location-specific wage premiums using survey data but rely solely on observed worker attributes—such as education, housing status, and age— without worker fixed effects. The availability of a worker-level panel from the Thai LFS allows us to overcome this key limitation in specification 3.

The term $\eta_{c,s(i,t),t}$ captures tambon-and-industry specific attributes, commonly referred to as localization economies which include factors such as number of establishments in industry $s(i,t)$ within a tambon, their employment shares and the share of skilled workers within industry-tambon pairs. We could account for localization economies using two options. First, we can construct these indicators at the industry–tambon level from the economic censuses and include them as controls in the above specification. However, because Thai manufacturing and business censuses are available for 2012, 2017 and 2022, respectively, these indicators would have to be interpolated in intervening years in our sample. Moreover, for establishments with fewer than 10 workers, the Thai firm censuses follow a sampling protocol rather than a full enumeration. In cases where employment in an industry-tambon is limited to firms below 10 workers, the representation of an industry-tambon pair in the census is left to chance and determined by random sampling. As a result, while these pairs may be observed in the LFS, they may not appear in the census data, creating missing data.

To address these limitations associated with firm censuses data, our preferred approach is to instead include industry–district–year fixed effects. This specification controls for common industry shocks across tambons within a district and year, including those that are not observed in the firm censuses. The assumption here is that industrial-

interactions at the district level are a reliable proxy for industry-specific interactions at the sub-district (tambon) level. Indeed, across years for which firm-censuses are available, we find that district-industry-year fixed effects can explain 72% of the variance in worker–population shares at the industry–tambon–year level, indicating that these fixed effects can go a long way in controlling for typical measures of localization economies at finer tambon levels.

For rental costs, we follow Combes, Duranton, and Gobillon (2019) to recover costs at the tambon level through the specification:

$$\log R_{it} = \psi_{c(i),t} + X_{i,t}\beta + \epsilon_{i,t}, \tag{4}$$

where R_{it} denotes rental costs or rental expenditure shares from the SES. The vector $X_{i,t}$ includes detailed dwelling and household characteristics: log monthly per capita consumption, household size, dwelling type, construction materials, tenure status, whether the unit hosts a business, number of rooms and bedrooms, access to electricity, cooking fuel, drinking water source, water supply type, garbage disposal method, toilet facility, municipal status, and the household's yearly percentile rank in the consumption distribution. The term $\psi_{c(i),t}$ captures the tambon-specific component of rent after conditioning on household and housing characteristics, and can be interpreted as the average cost of housing faced by a representative dwelling unit in a given tambon and year.

4.2 Estimating the Effect of Aging on Wage Premiums and Rental Costs

With estimated tambon-level wage premia $\hat{Z}_{c,t}$ and urban cost estimates $\hat{\psi}_{c,t}$ in hand, we examine their relationship with local population aging. Our estimating equations, specified in first differences, are:

$$\begin{aligned} \Delta\hat{Z}_{c,t} &= a^{agg}\,\Delta\frac{E_{c,t}}{N_{c,t}} + \delta^{agg\prime}\Delta n_{c,t} + D_{d(c),t} + e_{ct} \\ \Delta\hat{\psi}_{c,t} &= a^{cost}\,\Delta\frac{E_{c,t}}{N_{c,t}} + \delta^{cost\prime}\Delta n_{c,t} + D_{d(c),t} + e'_{ct} \end{aligned} \tag{5}$$

where $E_{c,t}/N_{c,t}$ is the share of the population aged 65 and above in tambon c at time t, and $n_{c,t}$ denotes population. The coefficients of interest, a^{agg} and a^{cost}, measure the effect of a change in the elderly share on productivity premia and living costs, respectively, holding population growth fixed.

Time-varying local amenities can jointly determine demographic composition, wages

and rentals. Tambons with greater amenity endowments command higher rents and wage premia, and changes in amenities may themselves can differentially affect demographic groups (Giannone et al., 2023). We address this by including district-by-year fixed effects $D_{d(c),t}$, where $d(c)$ denotes the district containing tambon c. These absorb any time-varying shocks common to tambons within a district—such as the opening of a tertiary medical center serving a cluster of nearby tambons—so that identification comes from differential changes in the elderly share across tambons within the same district and year.

All changes in productivity, costs, elderly shares, and controls are constructed as deviations from the tambon's first year in the sample:

$$\Delta X = X_{c,t} - X_{c,t_0},$$

where t_0 denotes the first year in which tambon c enters the panel. The LFS follows a tambon for six quarters before rotating it out, with tambons randomly reselected in later years. Long-period differencing therefore produces an approximately uniform distribution of time spans ranging from one to fifteen years, as shown in Appendix Figure A4. The SES, by contrast, tends to revisit tambons in consecutive years, with fewer revisits over longer horizons.

4.3 Instrumental Variables Specification

To identify the causal effect of rising elderly population shares on tambon-level productivity and costs, two sources of bias must be addressed. First, unobserved economic shocks may drive demographic change at the tambon level. A negative income shock, for instance, could induce out-migration of younger workers while older individuals—facing lower expected lifetime returns to migration—remain. OLS estimates would then be downward biased, understating the productivity of aging tambons[9].

Second, productivity shocks could themselves induce demographic responses, creating reverse causality. Positive productivity trends within a tambon may alter fertility decisions or improve life expectancy, so that local economic conditions endogenously drive the age structure rather than the reverse.

We address both concerns using two-stage least squares, instrumenting the elderly share following the strategy in Maestas et al. (2023).

The instrument is constructed as follows. The earliest year with tambon-level age-disaggregated population data from DOPA is 1998. To predict the number of individuals

[9]District-year fixed effects absorb shocks common to all tambons within a district. Any remaining confounding must therefore arise from shocks that differentially affect tambons within the same district.

aged 65 in tambon c in year t, we multiply the number aged $65-(t-1998)$ in that tambon in 1998 by the corresponding national cohort survival rate, defined as the ratio of the national population of that age in year t to the national population of the originating cohort in 1998. Repeating this calculation across the full age distribution up to age 100 yields a predicted elderly population for each tambon, based on its 1998 age structure and national cohort survival trends. Applying the same procedure to all ages starting from age zero in 1998 generates a predicted total population. The ratio of predicted elderly to predicted total population is our instrument.

To illustrate, predicting the elderly population in 2010 requires tracking individuals aged 53 in 1998 (who reach age 65 in 2010) through those aged 88 in 1998 (age 100 in 2010). The procedure is repeated for each subsequent year, extending the cohort survival window accordingly—from a 12-year gap for 2010 to a 21-year gap for 2019, the final year of the sample.[10]

The instrument follows a Bartik-style design in the sense of Goldsmith-Pinkham, Sorkin, and Swift (2020): geographic variation in 1998 cohort sizes provides the "shares," while national cohort-specific survival rates since 1998 provide the "shifts." The identifying assumption is that a tambon's 1998 age composition affects subsequent changes in productivity and urban costs only through its effect on the realized age structure. In our specification, this requires that the 1998 demographic distribution be uncorrelated with within-district economic trends over any span of years between 2004 and 2019. We assess the plausibility of this assumption through the robustness checks discussed below.

Formally, we aggregate elderly and total populations across age-groups j at location c and year $t \in [2010, 2019]$ using:

$$\tau = t - 1998$$

$$\hat{E}_{c,t} = \sum_{j=65-\tau}^{100-\tau} N_{j,c,1998} \, \frac{N_{j+\tau,\text{Thailand},t}}{N_{j,\text{Thailand},1998}}$$

$$\hat{N}_{c,t} = \sum_{j=0}^{100} N_{j,c,1998} \, \frac{N_{j+\tau,\text{Thailand},t}}{N_{j,\text{Thailand},1998}}$$

Summing the predicted populations for each tambon-year, we construct the instrumental variable as

[10]Cohorts not yet born in 1998 cannot be predicted. By 2019, the predicted total population excludes individuals aged 21 and younger. This omission likely attenuates first-stage power but does not compromise instrument validity.

$$\Delta \frac{\hat{E}_{c,t}}{\hat{N}_{c,t}} = \left(\frac{\hat{E}_{c,t}}{\hat{N}_{c,t}} \right) - \left(\frac{\hat{E}_{c,t_0}}{\hat{N}_{c,t_0}} \right) \tag{6}$$

Note that changes in population density, entering the specification as a control variable, are themselves endogenous, subject to the same omitted variable and reverse causality concerns as the elderly share. We therefore instrument both the elderly share and population density using the predicted populations described above.

Before turning to estimation results, we summarize the theoretical predictions that guide our interpretation of a^{agg} and a^{cost}. Section 3 yields a clear prediction. At any given population growth rate Δn, an increase in the elderly share — implying a reduction in birth rates since $n = \beta - \mu$ and a weakening of generational turn over term in equations (1) and (2) — raises per capita consumption and capital accumulation. Higher local consumption and savings generate greater local demand, which—through the demand-linked circular causality —strengthens agglomeration forces and bids up wage premiums and rental costs. Our model therefore predicts that rising elderly shares increase both the productivity premium ($a^{agg} > 0$) and the rental cost estimate ($a^{cost} > 0$).

5 Empirical Motivation: Aging Locations Experience Higher Wage Premia and Rents

We begin by estimating $\hat{Z}_{c,t}$ and $\hat{\psi}_{c,t}$. Given the large number of tambons in Thailand, reporting tambon–year fixed-effect coefficients is impractical. Instead, Table 1 presents key moments of the variables used in estimating equations (3) and (4).

The variance of log hourly wages and log monthly rentals across the sample is 0.769 and 0.544, respectively. Individual time-invariant characteristics account for 53% of the variation in wages, while age and its square explain 17% and 11%, and occupational category contributes 5%. Location-specific industrial characteristics, by contrast, account for 80% of the observed variation in log wages, with tambons alone and residuals explaining 9% of the variation. Replacing the district-industry-year effects with standard proxies for localization economies – the number of establishments in an industry-tambon pair, the industry employment share, and the share of skilled workers, all derived from the economic censuses – does not materially alter the contributions of other factors to observed wage variation. This is expected because approximately $\frac{2}{3}$ variation in industry-location trends at tambon-level is absorbed by flexible district-year term.

In terms of urban costs, tambon-level attributes explain 25% of the variation in

rental values, followed by household per capita consumption (11.7%) and dwelling characteristics—particularly the number of rooms (4%). The residual term accounts for 23.4% of the variance in log rentals.

Productivity		**Costs**	
Variance of log hourly wage	0.769	Variation in log rental values	0.544
Tambon-year ($Z_{c,t}$)	9.4%	Tambon-year ($\psi_{c,t}$)	24.64%
Industry-tambon-year ($\eta_{c,s,t}$)	79.8%	Rural/Urban	0.42%
Individual characteristics		*Dwelling characteristics* ($X_{i,t}$)	
Age ($X_{i,t}$)	16.5%	Type of Dwelling	0.21%
Age-squared ($X_{i,t}$)	11.3%	Materials of construction	0.88%
Occupation-year ($X_{i,t}$)	4.7%	Tenure	1.17%
Individual fixed effect(u_i)	52.8%	Business uses	1.00%
Residual	8.7%	Number of rooms	3.89%
		Electricity	0.06%
		Cooking Fuel	0.00%
		Drinking water	0.11%
		Water supply	0.09%
		Garbage disposal	0.02%
		Toilet facility	0.08%
		$\beta\times$ Log monthly consumption pc	11.73%
		$\beta\times$ Household size	1.13%
		Residual	23.43%

Table 1: Decomposition of variation in log wages and rental values by explanatory variables
The first row of the table shows the variance in log hourly wages and log rental values across years. The percentages in the remaining rows denote the share of variance attributed to explanatory variables. The β term reflects the contribution of the variance of the continuous variable multiplied by its regression coefficient. Samples exclude singletons.

5.1 The Impacts of Aging on Household-level Outcomes

Figure 3 visualizes the IV design. The figures in the top panel show OLS estimates, underscoring the positive relationship between increasing elderly population share, productivity and rental costs, controlling for changes in population density and district-year time trends. The slope of the fitted line is estimated to be positive and significant in both figures. The middle panel underscores the strength of the instrumental strategy using DOPA's age-wise disaggregated data from 1998 with strong t-statistics. Finally, the bottom panel shows the positive and significant reduced-form relationship between changes in productivity, rental costs and predicted changes in elderly shares, consistent with OLS, consistent with the OLS figures.

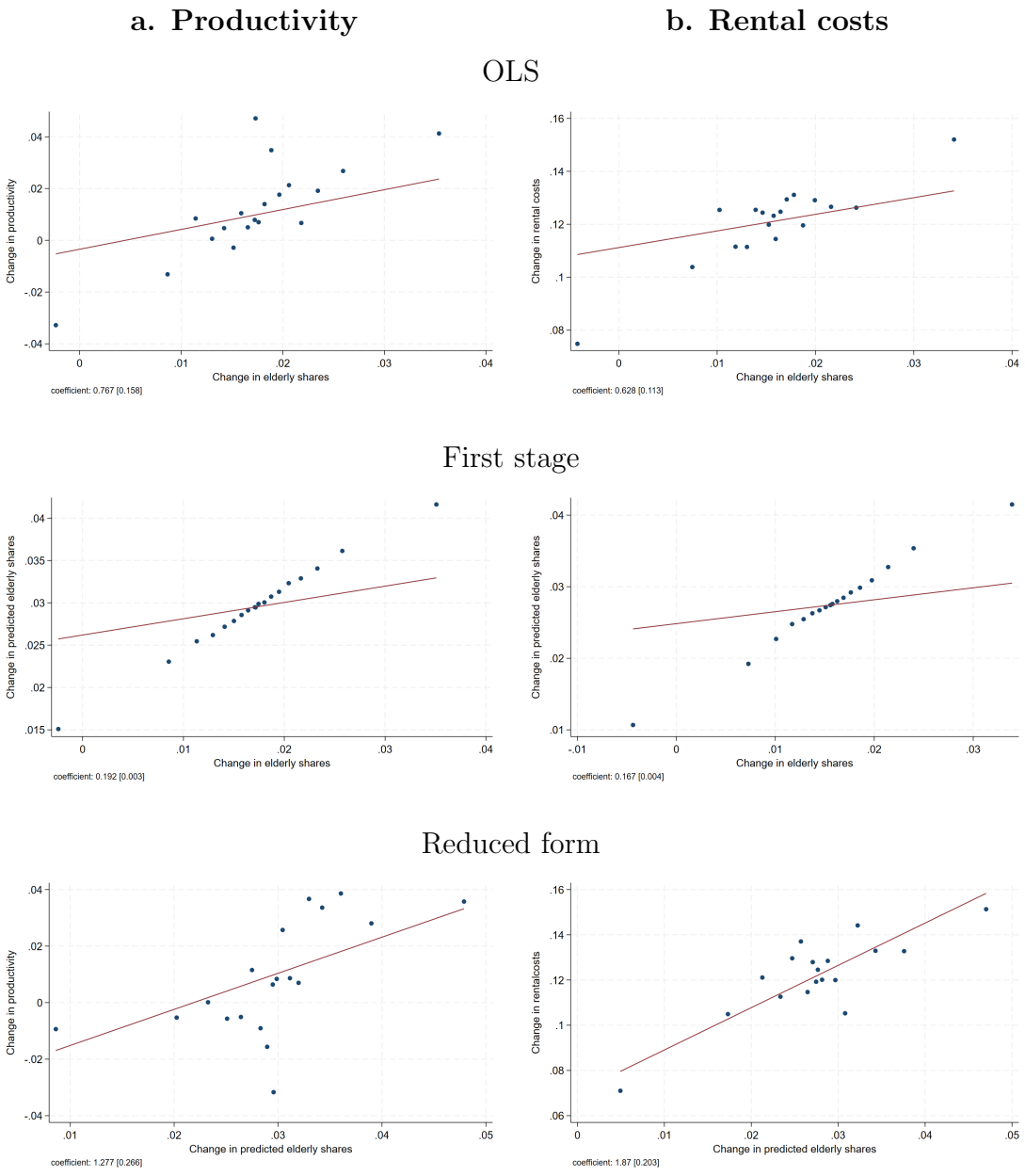


Figure 3: Summary of the research design
The unit of observation is a tambon-year. Productivity, $\hat{Z}_{c,t}$, is estimated using equation 3, and rental costs, $\hat{\psi}_{c(i),t}$, are obtained from equation 4. Each scatterplot displays 20 equally sized bins constructed using Stata's *binscatter* command. All specifications include changes in population density as controls and district-year fixed effects.

Table 2 reports the main results for the productivity premium. Following Conley (1999), we allow for spatial dependence of unknown form across tambons within a 500 km radius and serial correlation with a lag of up to five years.

The OLS estimate in column (1) is 0.767 and statistically significant at conventional levels. Column (2) presents the baseline IV results, instrumenting changes in both the elderly share and population density using equation (6). The 2SLS coefficient implies that a one percentage point increase in the elderly share raises the local productivity premium by approximately 2.3 percent, and the strong F-statistic confirms the strength of the instrument variable.

Column (3) augments the specification with controls for changes in log internal Thai migrants and log non-Thai population at the tambon level. The point estimate rises marginally to 2.655, implying that a one percentage point increase in the elderly share raises productivity by approximately 2.7 percent at the sample mean. The first-stage F-statistic remains strong and we treat this as our preferred specification.

The 2SLS estimates in columns (2) and (3) exceed the OLS estimate, consistent with downward bias in OLS from unobserved negative productivity shocks driving out younger-workers from tambon, resulting in simultaneous decreases in productivity and higher elderly shares. If the identifying assumption — that a tambon's 1998 age composition is uncorrelated with subsequent economic shocks conditional on district-year fixed effects — holds, the IV estimate should be stable to the inclusion of additional controls for economic outcomes that vary within a district. Columns (4), (5) and (6) test this by adding tambon-level amenities from OpenStreetMap (as of 2025), geographic polynomials – interacting tambon latitude and longitude with year dummies to absorb unobserved trends that vary smoothly across space — and, by controlling for changes in nighttime lights which serve as proxy for local economic growth. None of these additional variables materially shifts the coefficient relative to column (3), providing confidence that our 1998 predicted elderly share is uncorrelated with subsequent within-district economic trends.

Table 3 reports estimates of the response of rental costs to changes in the elderly share. As with productivity, the OLS estimate in column (1) is smaller than the IV estimate in column (2), consistent with downward bias from unobserved confounders. Adding migration controls in column (3) marginally affects the coefficient and moderately reduces the first-stage F-statistic. Notably, log migration enters with opposite signs in the two specifications—positive for productivity in the table above and negative for rental costs below —consistent with anticipated positive correlations between migration and productive locations and negative correlation with high-cost ones. Columns (4), (5) and (6) incorporate observed amenities from OSM, time-varying geo-

	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
$\Delta \frac{E_{c,t}}{N_{c,t}}$	0.767***	2.288**	2.655***	2.767***	2.766**	2.741***
	(0.278)	(0.972)	(0.998)	(0.993)	(1.162)	(1.012)
$\Delta n_{c,t}$	0.000***	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai			-0.008	-0.008	-0.008	-.0074786
			(0.006)	(0.006)	(0.006)	(0.006)
Δ log migrant			0.016**	0.016**	0.016*	.016**
			(0.007)	(0.007)	(0.008)	(0.007)
Food Beverages				0.001	0.001	
				(0.001)	(0.001)	
Health				0.003	0.003	
				(0.002)	(0.002)	
Hotels				-0.001	-0.001	
				(0.001)	(0.001)	
Retail				-0.001	-0.001	
				(0.002)	(0.002)	
Transport				-0.002	-0.002	
				(0.001)	(0.001)	
Δ NTL						-0.000
						(0.000)
N	28433	27962	27962	27962	27962	27962
F-statistic	.	706.728	527.150	570.181	548.637	480.803
District X Year FE	✓	✓	✓	✓	✓	✓

Table 2: Impact of elderly shares on productivity

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\Delta \frac{E_{c,t}}{N_{c,t}}$ indicates the change in share of elderly population within tambon and $\Delta n_{c,t}$ change in population density. Column (5) supplements the specification in (4) by tambon latitude and longitude interacted with year. Column (6) controls for changes in night-time light intensity at the tambon level. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

graphic controls and changes in night-time lights to check if the coefficient is sensitive to variables that may be correlated with local economic growth. None of these controls materially alter the estimated coefficient.

Our preferred specification in column (3) implies that rental costs rise by approximately 2.59 percent for a 1 percentage point change in average elderly shares. The point estimates suggest productivity rises somewhat more than costs, consistent with the rental expenditure share declining. Appendix Table A5 shows this to be the case. The coefficient on the elderly share in column (3) implies that a percentage point increase in the average elderly share reduces the rental expenditure share by 0.6 percentage points. Estimates are robust to adding controls that are correlated with local economic shocks — amenities, geographic polynomials and changes in nighttime lights — further speaking to the validity of the identification assumption.

5.2 Robustness

Short-versus-medium term effects. The preceding estimates pool changes constructed over varying time horizons, since changes are relative to the first year each tambon enters the sample. We now examine whether the estimated effect differs systematically across short and long horizons.

Figure 4 implements the above specification by progressively expanding the sample from changes constructed over one-year intervals to those spanning longer periods. At horizon h, the sample includes all tambons observed within one to h years of their earliest appearance in the LFS or SES. Because demographic composition evolves slowly, differencing over shorter windows imply smaller changes in the elderly share: at the one-year horizon, the average change in elderly share is less than 0.5 percentage points. Pooling intervals of up to 10 years raises the average change to approximately 1 percentage point, while including all available observations—spanning up to 15 years—increases it to roughly 1.6 percentage points.[11] The figure reports both the estimated coefficient and the average change in elderly share within the sample.

At the one-year horizon, the average change in elderly share is approximately 0.2 percentage points and the estimated effect on the productivity premium is small and statistically insignificant (panel (a)). The coefficient turns positive and statistically significant once the average change in elderly share reaches approximately half a percentage point, corresponding to intervals of up to four years. The coefficient moderates thereafter as longer horizons are included in the sample, stabilizing at approximately

[11] We pool across year spans rather than estimating regressions at each year span because number of observations at each year-cell are small. With fewer observations, the instrument weakens, making it difficult to distinguish a null result from one driven by insufficient first-stage power.

	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
$\Delta \frac{E_{c,t}}{N_{c,t}}$	0.628***	3.340***	2.591***	2.351**	2.311**	2.462**
	(0.193)	(0.957)	(1.001)	(0.998)	(1.107)	(0.980)
$\Delta n_{c,t}$	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai			0.006	0.006	0.006	0.006
			(0.006)	(0.006)	(0.006)	(0.006)
Δ log migrant			-0.015***	-0.016***	-0.016***	-0.015**
			(0.006)	(0.006)	(0.005)	(0.006)
Food Beverages				0.000	0.000	
				(0.001)	(0.001)	
Health				-0.003	-0.003	
				(0.002)	(0.002)	
Hotels				0.000	0.001	
				(0.001)	(0.001)	
Retail				-0.001	-0.001	
				(0.002)	(0.002)	
Transport				0.003**	0.003***	
				(0.001)	(0.001)	
ΔNTL						0.000
						(0.000)
Constant	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	19742	19409	19409	19409	19409	19409
F-statistic	.	557.291	334.060	351.704	366.142	278.750
District X Year FE	✓	✓	✓	✓	✓	✓

Table 3: Impact of elderly shares on rental costs

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\frac{E_{c,t}}{N_{c,t}}$ indicates the share of elderly population within tambon and $\Delta n_{c,t}$ change in population density. Column (5) supplements the specification in (4) by tambon latitude and longitude interacted with year. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

2.7 percent as the mean change in elderly share reaches 1.6 percentage points over 15-year intervals. This pattern suggests that small changes in elderly shares, say over a 1 year period, are insufficient to generate detectable productivity effects, likely because the consumption and capital accumulation needed to activate the agglomeration mechanism takes time.

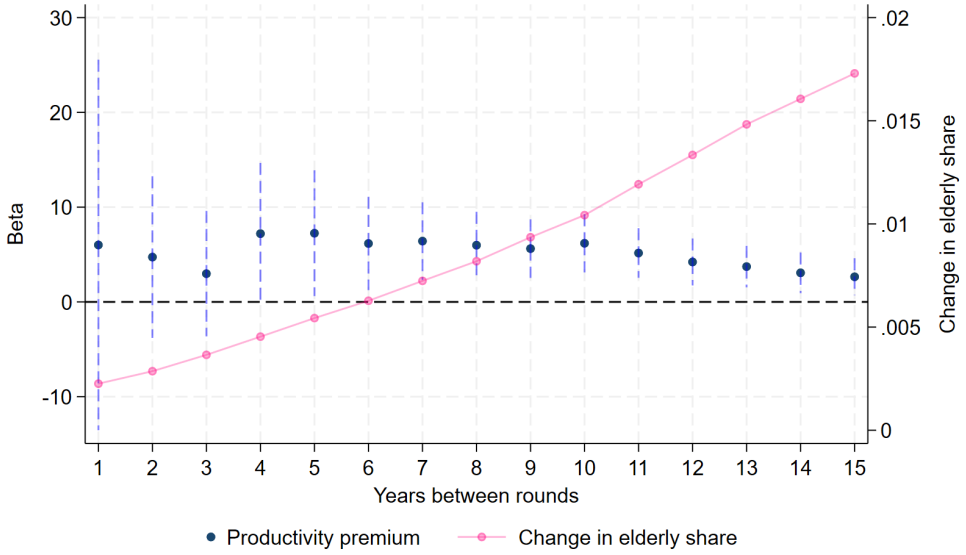
Rental costs exhibit a similar pattern (panel (b)). Coefficients at short horizons are small and imprecisely estimated, becoming statistically significant only once changes in elderly shares average approximately one percentage point, at around the five-year horizon. Thereafter, the rental cost coefficient remains stable at approximately 2.6 percentage points per one percentage point rise in the elderly share, irrespective of further increases in the average change arising from longer differencing windows. Rental expenditure show similar patterns (Appendix Figure A5): short-horizon effects are indistinguishable from zero, impacts emerge once elderly shares have risen by more than half a percentage point, and the estimates stabilize as the differencing window expands further.

Sensitivity to outliers. A potential concern is that the results may be driven by tambons with unusually large changes in elderly population shares or in the predicted elderly shares derived from the 1998 age distribution.[12] A related concern arises from the survey-based construction of the productivity premium, rental costs, and rental expenditure share, whose tambon-level estimates may be disproportionately influenced by extreme sampling observations.

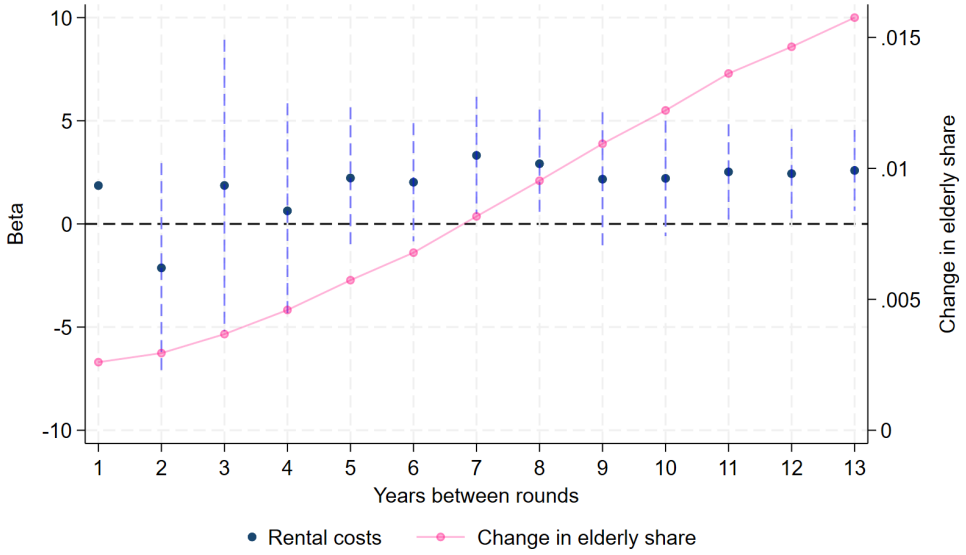
To examine this possibility, Appendix Table A6 reports estimates after trimming observations below the 5th and above the 95th percentile of each change variable, with percentiles computed separately within each time horizon. Columns (1) through (7) respectively exclude outliers in changes in the elderly share, predicted changes in the elderly share, changes in the productivity premium, observed changes in density, predicted changes in density, and changes in the non-Thai and Thai migrant populations. Column (8) excludes outliers along all of the above dimensions jointly. Across all specifications, the estimated coefficient remains positive and statistically significant, with the exception of column (8), where the most restrictive joint exclusion criterion attenuates the estimate and significance is lost. First stage F-statistic is strong across all outlier checks and the implied effect of a percentage point rise in elderly share ranges between 1.3% to 3.4% across specifications – meaning that our main estimate of 2.6% falls within this range of outlier analysis.

Appendix Tables A7 and A8 repeat this exercise for rental costs and rental expendi-

[12]Since predicted population is constructed by applying national cohort survival rates to the 1998 tambon-level age distribution, tambons with outlying predicted counts are effectively those with outlying age-group shares in 1998.



(a) Impact of elderly shares on productivity



(b) Impact of elderly shares on urban costs

Figure 4: Impact of changes in elderly share over time horizon
Notes: The horizontal axis denotes the maximum differencing window included in the estimation sample. At horizon h, the sample comprises all tambons reinterviewed within h years of their first appearance. The spike shows 95 percent confidence intervals based on Conley (1999) standard errors that allow for spatial and serial correlation of the error term. All specification instrument for changes in population density and include controls for changes in migration.

ture shares. Rental costs rise significantly with the elderly share across all specifications, including the specification that jointly reduces outliers across all variables. The implied effects on rental costs ranges between 2.2% to 3.7% – with our main estimate sitting between these range of estimated effects. Similarly, rental expenditure shares in these outlier analysis range between -0.5 to -0.7 percentage points across specifications.

Sensitivity to different elderly age groups. Thus far, we have defined the elderly as individuals aged 65 to 100. Figure 5 evaluates the sensitivity of results by changing this definition at five-year intervals starting 55 to 90. The two panels display estimated effects on the productivity premium and rental costs; Appendix Figure A6 reports corresponding results for the household rental expenditure share.

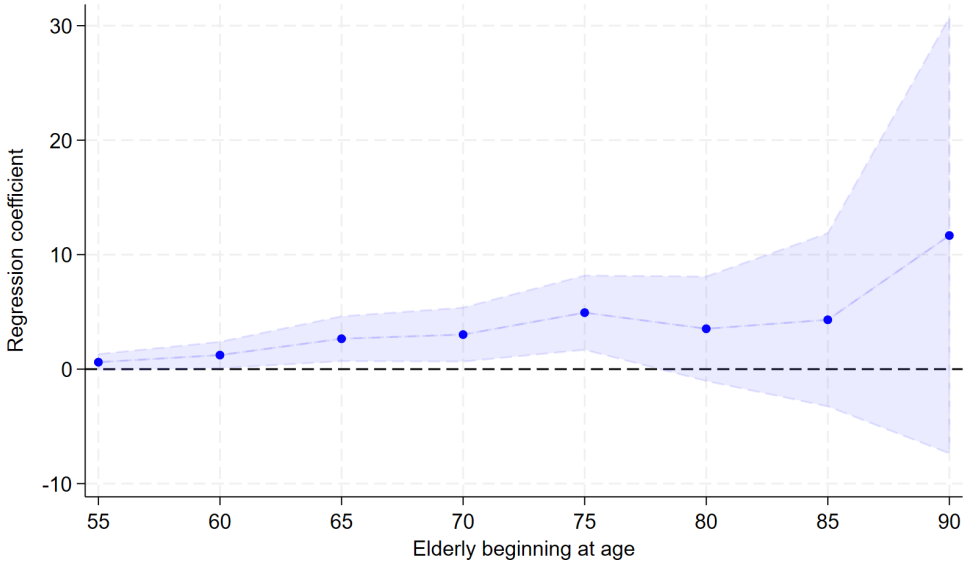
Elderly shares definitions beginning at age 55 yield an insignificant effect on productivity but a significant 1.4% increase in rental costs and a 0.3 percentage point decline in rental expenditure share. Thereafter, elderly groups starting ages 60 to 75 yield progressively higher estimates: between 1.2% to 5% for productivity, 2.1% to 5% for rental costs, and declines in rental expenditure share by 0.3 to 1.4 percentage points, all statistically significant. Beyond age 80, the coefficients become imprecise.

These results suggest that the positive effects on productivity and rental costs are progressively rise between ages 60 to 75. This is likely because populations older than 75 will be less unable to sustain the strong demand-side channels needed to sustain agglomeration gains.

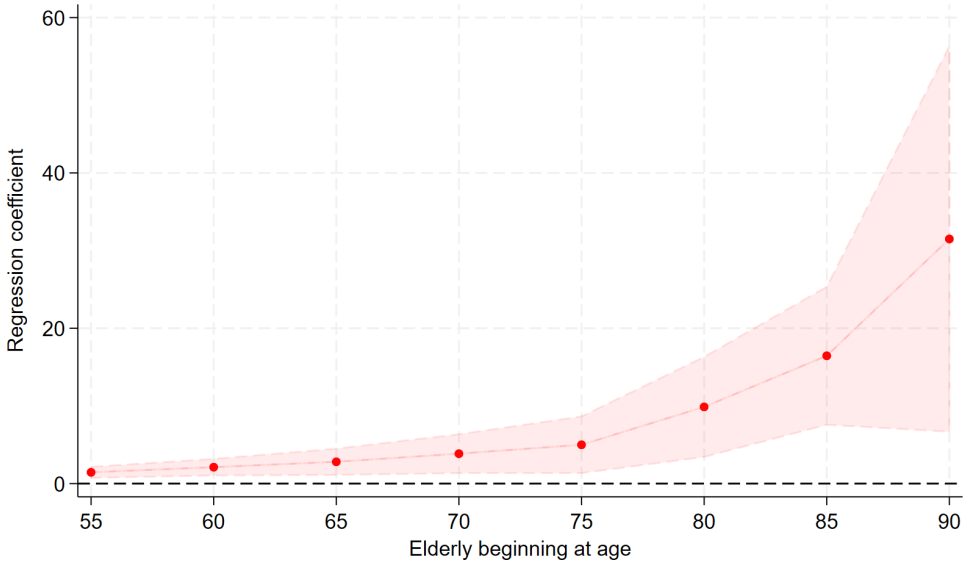
Sensitivity to log specification, clustering level, and mis-specification tests. Column (1) to (3) of Appendix Table A9 reports estimates from a log-log specification, regressing the change in log productivity premium on the change in log elderly share. The coefficient implies that a 1% increase in the elderly share is associated with a 0.137% rise in the local productivity premium, a 0.95% increase in rental costs, and a 0.045% reduction in the rental expenditure share.[13]

Next, we return to the baseline level-log specification and examine sensitivity to alternative assumptions about the error correlation structure. Appendix Table A10 reports estimates with standard errors clustered at the district and province levels. For the productivity regressions, district-clustered standard errors exceed province-clustered standard errors, suggesting that productivity shocks are more strongly correlated across tambons within the same district than across tambons within the same province but different districts. The pattern reverses for the rental specifications. First-stage F-

[13]The mean elderly share in our sample is 0.076, so a 1 percentage point change represents a 13.2% change at the mean. Scaling the log-log elasticity accordingly, a 1 percentage point increase in the elderly share implies a 1.8% rise in productivity ($=0.137 \times \frac{0.01}{0.076} \times 100$), comparable to the 2.7% estimate from the semi-elasticity specification. The implied effects from the log-log specification on rental costs (2.6% increase) and the rental expenditure share (0.6 percentage point decline) for the same 1 percentage point change are similarly consistent with the estimates reported earlier.



(a) Productivity premium



(b) Rental costs

Figure 5: Effects by elderly age groups
Notes: The horizontal axis shows the definition of elderly: at age beginning h, the elderly share comprises of all ages between h to 100. The regression coefficient is on the left vertical axis. The shaded area 95 percent confidence intervals based on Conley (1999) standard errors that allow for spatial and serial correlation of the error term. All specification instrument for changes in population density and include controls for changes in migration and non-Thai population.

statistics under district clustering are approximately half those under province clustering, and roughly one quarter of those reported in the main results — a large portion of the instrument's variation is within-district common variation rather than independent tambon-level variation. District-clustered standard errors therefore represent the more conservative analytical benchmark in our setting, and the estimated effects retain statistical significance under this specification.

Finally, the heterogeneous effects across age groups documented in Figure 5 raise a potential mis-specification concern for the pooled Bartik estimator. As Goldsmith-Pinkham et al. (2020) show, the Bartik estimator can be expressed as a weighted combination of just-identified IV estimators — in our setting, one for each cohort group (ages 65–69, 70–74, 75–79, 80–84, 85–89, 90–94, and 95–100). If the predetermined population of any cohort is endogenous to subsequent local economic growth, and that cohort receives substantial weight in the Bartik aggregation, the pooled estimator may fail the exclusion restriction. The heterogeneous effects in Figure 5 are therefore relevant not only as a substantive finding but also as a diagnostic: if they reflect the endogeneity of a particular cohort rather than genuine variation in the aging-productivity relationship, the validity of the overall Bartik estimator would be compromised.

To examine this, Goldsmith-Pinkham et al. (2020) recommend two checks. First, they recommend estimating an overidentified 2SLS specification — which instruments the observed change in elderly share using predicted population shares for each cohort group — and comparing it against the Limited Information Maximum Likelihood (LIML)[14] and Heteroskedasticity-Robust Fuller (HFUL) estimators of Hausman et al. (2012).[15] Second, they recommend reporting overidentification test statistics for each estimator. The overidentification test evaluates whether the cohort-specific instruments identify a common parameter; rejection indicates that at least one cohort share violates the exclusion restriction. Substantial disagreement across the three estimators, or rejection of the overidentification test, would cast doubt on the validity of the pooled Bartik estimator.

Appendix Table A11 reports results for productivity premium (Panel A), rental costs (Panel B), and rental expenditure share (Panel C). Several patterns emerge. First, the overidentified 2SLS yields estimates that are broadly consistent with the just-identified

[14]The LIML estimator is inconsistent under heteroskedasticity combined with many instruments (Hausman et al., 2012). We therefore report estimates using the continuously-updated GMM (CUE) estimator of Hansen, Heaton, and Yaron (1996), which provides a heteroskedasticity- and autocorrelation-consistent alternative, clustering standard errors at the district level.

[15]The HFUL estimator is consistent under heteroskedasticity and many-instrument asymptotics. We implement it using the Stata package `mivreg` of Anatolyev and Skolkova (2019), which reports heteroskedasticity-robust standard errors; clustered standard errors are not supported. We partial out district-year fixed effects from the dependent variable, endogenous regressors, instruments, and controls prior to estimation.

Bartik estimator across all three outcomes. The largest discrepancy arises in the rental expenditure share, though it remains economically small. Second, the Bartik and CUE estimates are very close across all three outcome variables with the overidentified 2SLS and HFUL estimates also being similarly close to one another. Third, the overidentification tests fail to reject the null at the 5% level for both the 2SLS and CUE specifications across all three outcomes. The HFUL overidentification test, on the other hand rejects the null, though this result should be interpreted cautiously given that the `mivreg` implementation does not support clustered standard errors within administrative regions, and the substantial spatial correlation across districts documented earlier is therefore unaccounted for in the HFUL overidentification test.

Taken together, these results provide reassurance that misspecification concerns likely are limited and that the exclusion restriction underlying the Bartik IV strategy are plausibly valid.

*Sensitivity to changes in other parts of age-distribution.*Unobserved economic shocks may reshape the entire age distribution, introducing bias if changes in younger cohort shares independently affect outcomes — a violation of the exclusion restriction. To assess this, we augment the baseline specification with changes in population shares for five-year age bins spanning ages 30–55, instrumenting each bin's share using the same cohort-survival procedure applied to the 1998 tambon-level age structure and national survival rates. All endogenous variables — the elderly share, population density, and each younger age-bin share — are instrumented jointly and estimated via 2SLS. Appendix Tables A12, A13, and A14 report results for the productivity premium, rental costs, and rental expenditure share, respectively.

Across all productivity premium specifications, only the elderly share (ages 65–100) enters positively and significantly. Adding younger age-bin shares one at a time leaves the coefficient of interest essentially unchanged, with estimates ranging between 2.6 and 3% — comparable to the baseline. The rental expenditure share results are similarly stable, with the elderly share coefficient remaining close to the baseline estimate of -0.6 percentage points. For rental costs, including younger age groups renders the elderly share coefficient statistically insignificant, reflecting both a lower point estimate and greater imprecision.

These results provide additional support for the exclusion restriction. If the 1998 age structure affected outcomes through channels unrelated to elderly population growth — such as compositional shifts among younger cohorts — the inclusion of younger age-bin shares would be expected to attenuate the coefficient of interest. The absence of such attenuation in the productivity and rental expenditure share specifications, and the lack of any significant association between younger cohort shares and these outcomes,

is consistent with the baseline age structure operating on outcomes primarily through its effect on the elderly share.

Sensitivity to an alternate census-based instrument. To further assess IV validity, we construct an alternative instrument using historical census data. IPUMS microdata for Thailand are available for 1970, 1980, and 1990, but the 1980 census is representative only at the provincial level and district identifiers are unavailable for 1970. The earliest district-level age distribution we can construct is therefore from the 1990 census — 14 years before the start of our panel — which further mitigates concerns that baseline age composition reflects pre-existing economic trends.

We follow the same cohort-survival procedure as the earlier analysis to construct our instrumental variable: the 1990 district-level age distribution is interacted with national cohort survival rates to generate predicted elderly shares for each sample year, and district-level changes in predicted elderly shares are computed relative to the first year each tambon enters the panel. Because the census data are only available at the district level, tambon-level changes in the elderly share are instrumented using district-level predicted changes.

Table A15 reports the results. The productivity coefficient is 2.27 percentage points, similar to the estimates reported above, and the rental-share elasticity is -0.571, also comparable. The rental cost estimate, however, is notably higher than under the DOPA-based instrument. The district-level instrument is expectedly weaker — reflecting both the coarser geographic aggregation and the longer time lag — but the consistency of the productivity and rental-share estimates reassures us that the positive effects of aging are not an artifact of the DOPA data.

Having documented that aging areas display higher wage premia and rents, we now examine which mechanism accounts for this pattern, testing labor supply, demand, and capital deepening in turn.

6 Examining the Role of Labor Supply

The canonical mechanism linking population aging to local economic outcomes is a contraction of labor supply. As the workforce shrinks, output falls (Aiyar et al., 2017; Fernández-Villaverde et al., 2025). Under scarcity of labor, the marginal product of the remaining workers rises, so that wages increase without any change in local productivity. Maestas et al. (2023) find that aging reduced U.S. state-level GDP per capita growth through both slower growth in output per worker and a decline in the employment rate. This mechanism poses a direct challenge to our interpretation centered around rising productivity: the wage premium documented in Section 5 could reflect labor scarcity

— a movement along a downward-sloping local labor demand curve — rather than an outward shift in labor demand generated by aging-induced capital deepening.

In this section, we explore the competing labor scarcity channel. A scarcity-driven premium requires the equilibrium quantity of labor to fall: as the elderly share rises, aggregate employment and total hours worked should decline. An outward shift in labor demand, by contrast, should raise wages with employment and hours stable or rising. Reduced slack — lower unemployment and underemployment — is consistent with *both* mechanisms, since a tighter market absorbs jobseekers whether supply has contracted or demand has expanded.

Table 4 reports seven labor-market indicators drawn from the LFS to diagnose the two channels. To avoid mechanically defining away an aggregate changes, all outcomes are measured as tambon-level counts rather than shares of population.[16] The indicators are total employed ("Employed"), persons outside the labor force("Out of LF"), unemployment, salaried employment, total hours worked ("Working Hours"), the number of workers reporting they want additional work ("Work More"), and the additional hours they would supply ("More Work Hours"). We report each for the full population (Panel A), the elderly (Panel B), and the working-age population (Panel C), retaining the instruments, controls, and district-year fixed effects from earlier specifications.

Three findings emerge from this analysis. First, there is no detectable changes at the extensive margin: a rise in the elderly share leaves total employment and salaried employment unchanged in the aggregate and among the working-age (Panel A and Panel C, columns 1 and 4). The rise in the out-of-labor-force count is confined to the elderly (Panel B, column 2) and reflects the mechanical accounting of older cohort being more likely to enter retirement rather than withdrawal by prime-age workers; the count of working-age out-of-labor-force individuals remains unchanged (Panel C, column 2). Second, there is no reduction at the intensive margin: total hours worked do not fall (column 5), and elderly employment and hours in fact rise (Panel B, columns 1 and 5), indicative of delayed-retirement among elderly consistent with Maestas and Zissimopoulos (2010). Third, the labor market tightens: unemployment falls, as do both measures of underemployment, with fewer working-age adults reporting a desire for additional work and a decline in the additional hours they would supply for these additional activities (columns 3, 6 and 7, Panels A and C).

A movement along a fixed labor demand curve requires the wage increase in Section 5 to be accompanied by falling employment and hours. Instead, we observe a rising

[16]Outcomes are collapsed from the repeated cross-section LFS to tambon-year totals, expressed in hundreds of thousands and weighted by sampling weights. This analysis uses the full repeated cross-section of the LFS to maximize coverage rather than the matched worker panel. Changes are computed relative to the first year a tambon appears in the LFS, following equation (5).

premium in the earlier section with employment and hours flat and slack declining in the below table. This indicates a potential outward shift in labor demand schedule — likely due to increased aging-induced savings that lead to local deepening of capital and increased labor demand. We do not claim that aging exerts no downward pressure on labor supply: the working-age employment and hours coefficients carry negative point estimates (Panel C, columns 1 and 5), though both are statistically indistinguishable from zero. Rather, any such pressure is absorbed by fuller utilization of the existing workforce — lower unemployment and underemployment — and by delayed retirement, without a net decline in labor input, so that scarcity cannot account for the observed wage premium.

Other than a outward shift in the demand curve, another possibility is that in-migration of working-age adults in aging tambons masks an underlying labor scarcity. This is unlikely due to three reasons. First, all specifications in Table 4 control for changes in the internal migrant and non-Thai populations from DOPA, so the estimated effects on employment and hours already account for changes in migration. Second, net replacement on the required scale is inconsistent with the observed intensity of internal migration in Thailand: over the five years to 2010, only 1.6 percent of Thais migrated between provinces, well below the pace at which local elderly shares are rising (Jampaklay, 2020). Refilling aging-induced labor supply gaps across the country through migration alone would demand net flows that are far higher than those observed. Third, we test the migration replacement hypothesis directly. In Appendix Table A16 we re-estimate the same diagnostics with the ratio of migrant to non-migrant totals as the dependent variable.[17] If migrant inflows were filling the labor gap left by aging, the migrant share of employment should *rise* in aging tambons. Appendix Table A16 shows the opposite: the migrant-to-non-migrant ratio of employment, non-participation, salaried employment, and hours falls as the elderly share rises.

7 Examining the Role of Local Demand Shocks

The wage and rent premia documented in Section 5 could also emerge from an aging-induced localized demand shock: older households consume more per capita than younger ones, so a rising elderly share raises expenditure on locally produced goods and services. Such a shock could raise wage bills and rents through an outward shift in the local demand curve, with no change in local productivity or agglomerations.

A localized demand response to aging is consistent with the theoretical predictions

[17] Changes in non-Thai and migration populations as controls are omitted from this specification, since the outcome is itself constructed from migrant status.

	(1) Employed	(2) Out of LF	(3) Unemployed	(4) Salaried	(5) Working Hours	(6) Work More	(7) More Work Hours
Panel A: Aggregate Labor Force							
$\Delta\frac{E_{c,t}}{N_{c,t}}$	0.019	0.336	-0.180***	0.482	-7.021	-0.371***	-9.638***
	(0.777)	(0.351)	(0.024)	(0.390)	(36.418)	(0.059)	(1.420)
$\Delta n_{c,t}$	-0.000**	-0.000	-0.000	-0.000***	-0.017**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)
Δ log non-thai	0.016***	0.004***	0.000	0.008***	0.730***	0.001***	0.027***
	(0.004)	(0.002)	(0.000)	(0.002)	(0.174)	(0.000)	(0.010)
Δ log migrant	0.002	-0.004	-0.000	0.007*	0.139	-0.001**	-0.028*
	(0.006)	(0.003)	(0.000)	(0.004)	(0.311)	(0.000)	(0.015)
Panel B: Elderly Labor Force (65+)							
$\Delta\frac{E_{c,t}}{N_{c,t}}$	0.118***	0.545***	0.001	0.014*	5.681***	-0.001	-0.067
	(0.046)	(0.116)	(0.001)	(0.008)	(1.878)	(0.003)	(0.066)
$\Delta n_{c,t}$	-0.000***	-0.000	-0.000	0.000	-0.001***	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai	0.001***	0.001**	0.000**	0.000	0.023***	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)
Δ log migrant	-0.000	-0.001	-0.000	0.000	0.000	-0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)
Panel C: Working Age Labor Force (15-64)							
$\Delta\frac{E_{c,t}}{N_{c,t}}$	-0.098	-0.210	-0.181***	0.468	-12.702	-0.370***	-9.571***
	(0.747)	(0.260)	(0.023)	(0.389)	(35.217)	(0.058)	(1.404)
$\Delta n_{c,t}$	-0.000**	-0.000	-0.000	-0.000***	-0.017**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)
Δ log non-thai	0.015***	0.003***	0.000	0.008***	0.707***	0.001***	0.026**
	(0.004)	(0.001)	(0.000)	(0.002)	(0.168)	(0.000)	(0.010)
Δ log migrant	0.002	-0.003	-0.000	0.007*	0.139	-0.001*	-0.028*
	(0.006)	(0.002)	(0.000)	(0.004)	(0.307)	(0.000)	(0.015)
N	34707	34707	34707	34707	34707	34707	34707
F-statistic	525.892	525.892	525.892	525.892	525.892	525.892	525.892
District X Year FE	✓	✓	✓	✓	✓	✓	✓

Table 4: Impacts on local labor market indicators

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a tambon-year. All outcomes are tambon-level counts (in hundreds of thousands), constructed by collapsing the repeated cross-section LFS using sampling weights, and differenced relative to the first year each tambon enters the sample. "Employed" is total employed persons; "Out of LF" is persons outside the labor force; "Unemployed" is persons seeking work; "Salaried" is wage and salaried workers; "Working Hours" is total hours worked; "Work More" is persons reporting they want an additional job; and "More Work Hours" is the additional hours they would supply. Panel A covers the full population, Panel B the elderly (65+), and Panel C the working-age population (15–64). All specifications simultaneously instrument changes in the elderly share and population density, control for changes in log migrant and log non-Thai populations, and include district-by-year fixed effects. Constant terms from each specification is suppressed for editorial reasons. Conley (1999) standard errors allow for spatial and serial correlation of the error term.

outlined in Section 3. The Grafeneder-Weissteiner and Prettner (2013) model predicts that because the elderly hold accumulated wealth and consume more than newborns, a fall in generational turnover raises regional per capita consumption and accelerates per capita capital accumulation. An increase in local expenditure is therefore consistent with one half of our theoretical framework. The second half, based on Baldwin (1999), predicts that higher local expenditure and rising capital rental rates generate agglomeration only when capital is imperfectly mobile. Under frictionless capital mobility, the incomes generated by a localized demand shock would flow freely to other regions, financing investment elsewhere and breaking the circular causality needed to sustain local agglomeration. This section provides evidence on the first of these two conditions; we take up the effect of aging on savings and investment under capital mobility frictions in Section 8.

To test for a local demand response, we construct tambon-level measures of nominal per capita household consumption from the SES[18]. We aggregate monthly household consumption expenditure to the tambon-year level, in total and separately for food, health, transportation, and education, and divide by the total number of household members surveyed in the tambon-year. Changes are computed in logs relative to the first year each tambon enters the SES, following equation (5). All specifications simultaneously instrument changes in the elderly share and population density, control for changes in the log migrant and log non-Thai populations, and include district-by-year fixed effects.

Table 5 reports the estimates. A one percentage point increase in the elderly share raises consumption per capita by 14.3 percent, confirming the prediction of the Grafeneder-Weissteiner and Prettner (2013) framework that locations aging faster record higher per capita expenditure. Food expenditure per capita rises by 23 percent and transportation by 10.7 percent, while education spending falls by 7.4 percent and health spending by 5.6 percent, at the 10 percent level.

A pure demand shock originating in elderly consumption would be expected to raise consumption of local services, and health care in particular. We find the opposite sign on health[19]. Because expenditure is measured in nominal terms, the estimates also combine quantity and price responses, and we cannot separate the two. These estimates establish that aging raises local demand, consistent with our theoretical framework. The increase is not, however, concentrated in the nontradable services whose demand should rise

[18]Spatially disaggregated price indices cannot be accessed in Thailand.

[19]The results on health and education deserve a cautious reading. The bulk of elderly health care in Thailand is financed through the public Universal Coverage Scheme, so household out-of-pocket expenditure recorded in the SES understates local demand for health services. The decline in education spending likely reflects the same fertility decline that raises the elderly share, which reduces the number of school-age children per household.

mechanically with an older population. This distinction matters for the establishment-level results that follow, which are estimated separately for tradable manufacturing and nontradable services. If the premia documented in Section 5 are generated by a pure local consumption shock, the firm-level response should be concentrated in the sectors serving that consumption. Section 9 examines the sectoral incidence of the firm-level response and returns to this question directly.

	(1) Consumption total	(2) Food	(3) Health	(4) Transportation	(5) Education
$\Delta \frac{E_{c,t}}{N_{c,t}}$	14.257***	22.970***	-5.588*	10.741***	-7.432***
	(1.808)	(2.920)	(2.884)	(1.464)	(2.466)
$\Delta n_{c,t}$	0.000***	0.000	0.001**	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai	-0.010	-0.020	0.031	-0.020	0.044*
	(0.010)	(0.014)	(0.029)	(0.013)	(0.024)
Δ log migrant	-0.022***	-0.005	-0.009	-0.035***	0.024
	(0.007)	(0.008)	(0.024)	(0.011)	(0.017)
Constant	-0.000	0.000	-0.000	-0.000	0.000
	(0.004)	(0.005)	(0.010)	(0.005)	(0.008)
N	19417	19412	18342	19416	18903
F-statistic	334.053	333.704	270.933	334.046	307.089
District X Year FE	✓	✓	✓	✓	✓

Table 5: Impact of elderly shares on per capita household consumption
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a tambon-year. The dependent variable in each column is the change in log nominal per capita household consumption expenditure, in total and by category, constructed by aggregating monthly SES expenditure to the tambon-year level using sampling weights and dividing by the total number of surveyed household members. Changes are taken relative to the first year each tambon enters the SES. All specifications control for changes in log migrant and log non-Thai populations and include district-by-year fixed effects. Conley (1999) standard errors allow for spatial and serial correlation of the error term.

8 Examining The Role of Savings and Investment

In Baldwin's (1999) framework, rising elderly shares cause agglomeration only when capital is imperfectly mobile: under frictionless mobility, aging-induced savings would be redistributed across Thailand and no spatial concentration would emerge. Appendix Table A4 shows that local savings and investment are correlated within Thailand, consistent with meaningful frictions in subnational capital mobility. This section establishes the causal mechanism—that rising elderly shares raise local investment through an increase in local savings in the presence of such frictions.

We implement the IV mediation framework of Pinto et al. (2020) and Dippel, Gold, Heblich, and Pinto (2022). The model is:

$$Z = \epsilon_Z \tag{7}$$

$$T = \beta_T^Z \cdot Z + \epsilon_T \tag{8}$$

$$M = \beta_M^T \cdot T + \epsilon_M \tag{9}$$

$$Y = \beta_Y^T \cdot T + \beta_Y^M \cdot M + \epsilon_Y \tag{10}$$

Together these decompose the effect of treatment T (change in the elderly share) on outcome Y (investment per capita) into a direct effect, DE $= \beta_Y^T$, and an indirect effect operating through mediator M (savings per capita), IE $= \beta_M^T \cdot \beta_Y^M$, with Total Effect TE $=$ DE $+$ IE. Identification is complicated by the fact that the error terms of the treatment, mediator, and outcome equations are correlated: aging, savings, and investment are jointly determined, ruling out approaches that assume full independence across equations. The Dippel et al. (2022) and Pinto et al. (2020) framework combines an instrument Z—in our case, the Bartik-style elderly-share instrument constructed from the 1998 DOPA registries—with restrictions on the error structure. The model permits $\epsilon_T \not\perp\!\!\!\perp \epsilon_M$ and $\epsilon_M \not\perp\!\!\!\perp \epsilon_Y$, so both T and M remain endogenous. The key assumption is that ϵ_T and ϵ_Y are uncorrelated conditional on M and the observed covariates, $\epsilon_T \perp\!\!\!\perp \epsilon_Y \mid M, X$, which Dippel et al. denote $\rho_{TY} = 0$.

We view this assumption as plausibly valid in our setting. The two leading threats to the independence of ϵ_T and ϵ_Y in the aging literature are reverse causality between demographic change and local economic conditions, and aging-induced contraction of the local labor market. The first motivates our Bartik-style instrument. The second is addressed directly in Table 4 shows that aging does not generate a detectable decline in the employment rate or the labor-force participation of the working-age population — only a reduction in their unemployment rate. With both of these channels accounted for, we are unable to identify a further mechanism that is orthogonal to savings and through which aging effects local investment independently of M, and we therefore maintain $\rho_{TY} = 0$ as plausibly valid in our case.

We use district-level data on savings and loans— interpret the latter as a measure of local investment—from the Bank of Thailand covering 2005–2022, and implement the IV mediation framework of Pinto et al. (2020) and Dippel, Gold, Heblich, and Pinto (2022). Because these data are unavailable at the tambon level, we aggregate our population measures and the Bartik-style instrument constructed from the 1998 DOPA registries to the district level. Following our earlier practice, we compute changes in investment, savings, and the elderly share relative to the first year each district appears

in the savings-and-loans dataset. Before turning to the mediation estimates, Appendix Figure A8 provides visual intuition for the relationship between changes in investment, savings, and aging at the district level. The top panel plots changes in district-level investment (in millions of baht) against changes in the predicted elderly share over the same period with predicted population density as a control. This reduced-form relationship between the instrument(Z) and outcome (Y) reveals a steadily positive relationship. The bottom panel repeats the exercise but controls for savings. The positive relationship disappears, indicating that once local savings is conditioned on, aging has a limited relationship with local investment growth.

Table 6 reports the estimates. Panel (a) presents Equations 8–10, and Panel (b) decomposes the total effect of aging on local investment into its direct and indirect components. Column (1) reports the baseline specification, which includes only changes in investment, savings, and the elderly share. Column (2) adds a control for the change in predicted population density. Columns (3) and (4) further add controls for changes in migration and the non-Thai population, and for changes in district-level nighttime lights. Column (3) is our preferred specification; Column (4) probes the conditional independence assumption $\rho_{TY} = 0$ by conditioning on nighttime lights as a proxy for district-level economic growth. The stability of the coefficients between Columns (3) and (4) is reassuring: if aging affected local investment through non-savings channels captured by broader economic growth, we would expect material movement across these columns. Column (5) drops Bangkok from the preferred specification.

The first row of Panel (a) documents a strong first-stage relationship between the instrument (Z) and district-level changes in the elderly share (T), mirroring the tambon-level results reported earlier. The second row reports the 2SLS estimate of the effect of aging on local savings (M): a 1 percentage point rise in the elderly share raises district-level savings by 11.5 million baht in the preferred specification.[20] Rows three and four report the estimates of Equation 10. Conditional on aging, a 1 million baht increase in local savings raises local investment (Y) by 0.85 million baht. The coefficient is identified by instrumenting changes in savings with the Bartik-style predicted elderly share, and its magnitude is consistent with frictions in within-country capital mobility: absent such frictions, local savings would be intermediated toward higher-return districts and β_Y^M would be expected to be close to zero. The coefficient on aging conditional on savings is negative in the preferred specification and remains negative once nighttime lights are included, lending further support to $\rho_{TY} = 0$: were non-savings components of local growth confounding the estimates, we would expect a material shift

[20] A 1 percentage point increase in the district-level elderly share takes approximately five years in our sample, implying an average annual increase in savings of roughly 2.3 million baht.

in β_Y^T between Columns (3) and (4). First-stage statistics for the mediator regression in Equation 9 exceed conventional thresholds, indicating strong instrument relevance.

Panel (b) brings these results together. The indirect effect operating through savings (**IE**) implies that a 1 percentage point rise in the elderly share raises local investment by 9.7 to 11 million baht across specifications. Excluding Bangkok cuts this coefficient by more than half, pointing to a significant role of the capital region in the savings-to-investment conversion, but the effect remains positive and statistically significant despite its exclusion. The direct effect (**DE**)—aging's impact on investment net of the savings channel—is −4.3 million baht. The total effect (**TE**) is 5.4 million baht, implying that the savings channel accounts for a share (**S**) of 1.8x to 2x of the total effect.

9 Impact on Firm-level Outcomes

To assess how population aging shapes key firm-level outcomes, we use establishment-level data from manufacturing censuses (2012, 2017, 2022) and services censuses (2012, 2022) conducted by the TNSO.

Following equation (5), we aggregate all firm level indicators at the tambon-year level and observe five outcomes at 5 and 10 year intervals, respectively for manufacturing and services sectors : (1) change in (log) revenue output per manhours of labor ($\Delta \log \frac{Y_t}{W_t}$), (2) change in annual investment as a share of capital value of fixed assets ($\Delta \frac{I_t}{K_{t0}}$)[21], (3) change in (log) annual wage bill per manhours of labor ($\Delta \log \frac{W_t}{L_t}$) (4) change in total number of workers (ΔL_t), and (5) change in worker concentration across establishments within a tambon using the Herfindahl-Hirschman index (ΔH_t). The unit of analysis is tambon-year and all specifications retain district-year fixed effects, include changes in migration and non-thai population as controls and simultaneously instrument for elderly shares and population density.

We retain establishments with at least one paid worker, effectively excluding own-account enterprises. Revenue, wage bill, and investment values are winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles within each census year. Since the censuses do not report output in physical quantities, we use revenue per worker man-hours, $\Delta \frac{Y_t}{M_t}$, as our measure of worker productivity. This measure likely understates true dispersion in plant-level productivity for two reasons: first, the measure is aggregated to the tambon level,

[21]Following, Levinsohn and Petrin (2003), investment is calculated as the difference between the book value of fixed assets — machinery, land and building and vehicles — at the beginning and end of the year in which census was conducted. We ignore depreciation (which would further increase the value of investment over the year) and scale investment(I) by the book value of capital fixed assets at the start of the year in which census was conducted(K_{t0}).

	(1) Baseline	(2) + ΔDensity	(3) + ΔMigration	(4) + ΔNL	(5) Excl. Bangkok
Panel (a): Equations					
Eq 8: β_T^Z	0.637***	0.623***	0.614***	0.623***	0.491***
	(0.051)	(0.046)	(0.075)	(0.074)	(0.022)
Eq 9: β_M^T	9.316***	8.592***	11.524***	10.982***	5.753***
	(2.876)	(2.681)	(2.822)	(3.221)	(1.384)
Eq 10:					
β_Y^M	1.218***	1.065***	0.845***	0.772***	0.770***
	(0.349)	(0.234)	(0.110)	(0.126)	(0.115)
β_Y^T	-6.772	-4.658	-4.325**	-3.715**	-0.249
	(5.414)	(3.778)	(2.065)	(1.874)	(0.505)
Kleibergen-Paap F	5.35	8.32	18.04	11.45	16.52
Observations	4,128	4,128	4,128	4,128	3,435
Panel (b): Decomposition					
TE : $DE + TE$	4.578***	4.488***	5.415***	4.761***	4.180***
	(0.637)	(0.629)	(0.745)	(1.130)	(0.943)
DE : β_Y^T	-6.772	-4.658	-4.325**	-3.715**	-0.249
	(5.414)	(3.778)	(2.065)	(1.874)	(0.505)
IE : $\beta_M^T \cdot \beta_Y^M$	11.351**	9.146***	9.740***	8.475***	4.429***
	(4.779)	(3.490)	(2.701)	(2.848)	(1.254)
S $= IE/TE$	2.48	2.04	1.8	1.78	1.06

Table 6: Mediation of aging's effect on local investment through local savings
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of analysis in all specification is district-year. Panel (a) reports estimates from the three equations of the mediation model. Eq. (8) is the first stage regressing observed elderly share (T) on Bartik-styled predicted elderly share instrument (Z) based on DOPA 1998. Eq. (9) is a 2SLS of district-level savings (M) on T, instrumented by Z. Eq. (10) is the conditional 2SLS of district-level loans/investment (Y) on M and T, with M instrumented by Z and T entering as a conditioning variable following Pinto et al. (2020) and Dippel et al. (2022). Panel (b) reports the decomposition of the total effect into the direct effect (DE $= \beta_Y^T$) and indirect effect (IE $= \beta_M^T \cdot \beta_Y^M$) mediated by through savings. $S =$ IE/TE is the share of the total effect of aging on investment operating through the savings channel. Model 1 is baseline without controls; Model 2 adds predicted population density; Model 3 adds migration and non-Thai population trends; Model 4 additionally controls for nighttime lights; and Model 5 excludes Bangkok province from model 3. Standard errors clustered at the province level.

smoothing establishment-level variation in revenue per hours of work; and second, unlike quantity-based productivity measures, our proxy does not net out producer-specific prices, which are generally lower for more productive units (Foster, Haltiwanger, and Syverson, 2008). Changes in investment as a share of the initial book value of capital, $\Delta \frac{I_t}{K_{t0}}$, serve as a proxy for unobserved changes in establishment-level productivity, as an optimizing firm would increase investment with rising productivity (Pakes, 1991). At the tambon level, the decision made by firms to expanding their capital base in anticipation of positive productivity shocks in the future. Finally, changes in the wage bill per man-hours, $\Delta \log \frac{W_t}{M_t}$, provide a quality-adjusted measure of labor input, if wages reflect the marginal products of heterogeneous workers (Syverson, 2011). Increases in average wages at the tambon level therefore proxy improvements in worker quality or local labor productivity. $\Delta \log L_t$ denote the number of workers while ΔH_t represents changes in Herfindahl-Hirschmann's index $= \Sigma_c s_{ict}^2$, where s_{ict} is the share of workers in establishment i, tambon c at year t.

Table 7 presents estimates for manufacturing (Panel A) and services (Panel B). In the manufacturing sector, a one percentage point increase in the elderly population share raises revenue per manhour by approximately 19% over a 5-year interval, implying an average annual increase of roughly 3.8%. No corresponding increase in the aggregate number of tambon-level workers is observed — the coefficient on log workers is statistically insignificant — suggesting that the revenue gain reflects higher worker productivity rather than than increases in man hours through a larger labor force. Consistent with this interpretation, the average wage bill per manhour rises by approximately 2.2% annually over the same interval, pointing to improvements in labor quality or worker productivity. Investment rates also rise: firms increase investment by an average of 3 percentage points annually per 1 percentage point increase in elderly share over the 5-year horizon. The concurrent rise in revenue productivity, wage bill per manhour, and investment rate is accompanied by an increase in the concentration of manufacturing workers at the establishment level with the Herfindahl index of concentration rising by an average of 2 percentage points per year.

The services sector presents a contrasting picture. A one percentage point increase in elderly share reduces services revenue per manhour by approximately 14% over a 10-year interval, or roughly 1.4% annually. The total number of workers in the services sector also declines, at an average rate of approximately 1.3% per year over the same horizon. The wage bill per manhour falls by about 3% annually, indicating a deterioration in labor quality or worker productivity. Neither investment rates nor establishment-level worker concentration respond significantly to changes in elderly population shares in the services sector and there is no statistically significant impact on agglomeration.

	(1) $\Delta \log \frac{Y_t}{M_t}$	(2) $\Delta \frac{I_t}{K_{t0}}$	(3) $\Delta \log \frac{W_t}{M_t}$	(4) $\Delta \log L_t$	(5) ΔH_t
Panel A: Manufacturing					
$\Delta \frac{E_{c,t}}{N_{c,t}}$	18.992***	15.787***	11.081***	3.566	10.334***
	(5.439)	(2.592)	(3.106)	(2.260)	(2.036)
N	7135	7132	6077	7135	7135
District × Year FE	✓	✓	✓	✓	✓
Panel B: Services					
$\Delta \frac{E_{c,t}}{N_{c,t}}$	-14.166***	0.207	-29.901***	-13.295***	0.475
	(2.323)	(0.456)	(6.198)	(4.036)	(0.503)
N	2738	4142	2738	4155	4155
District × Year FE	✓	✓	✓	✓	✓

Table 7: Impact of aging on firm outcomes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is tambon-year. Manufacturing estimates are based on five year differences between censuses 2012, 2017 and 2022 census while services estimates are based on decadal differences between 2012 and 2022 round. Sample includes establishment with more than 1 workers. Revenue (Y_t), investment (I_t) and the wage bill (W_t) at the establishment level are winsorized at 1 and 99 percentile levels at each census round. All three indicators are summed across establishments in a tambon. Revenue and wage bill is scaled by worker man-hours (M_t), while investment is scaled by the book value of fixed capital assets at the start of census year (K_t0). $H_{ct} = \Sigma_c(s_{ict})^2$ is Herfindahl-Hirschmann's index with s_{ict} the share of manufacturing workers in establishment i in tambon c at year t. L_t denotes total number of workers in a tambon. All specifications are estimated by simultaneously instrumenting changes in elderly share and change in population density with controls for changes in log migration and log non-Thai population. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

Consistent with earlier patterns, Appendix Figure A7 shows that labor productivity — proxied by revenue per manhour and wage bill per manhour — and the investment rate peak among cohorts aged 60 to 75, with estimates becoming imprecise and economically unstable beyond age 80. Changes in other parts of the age distribution similarly leave the estimates unaffected. Changes in population in other parts of the distribution does not materially impact our result. We incorporate changes in population shares at five-year age bins from ages 30 to 55 and find stable coefficients: revenue per manhour rises by approximately 20.1% over the 5-year interval (approximately 4% per year, compared to 3.8% in results above), the investment-to-capital rate increases by 16% (15.7% in the above results), and the wage bill per manhour rises by approximately 11% (11.1% in the main results). These results, reported in Appendix Tables A17, A18, and A19 respectively, show that it is changes in elderly population share that are driving the impacts and not other parts of the demographic distribution.

10 Conclusion

Fertility has fallen below replacement level in most countries, and combined with declining age-specific mortality, the share of elderly in the population is rising worldwide. The economic consequences of this demographic transition remain contested. One strand of the literature has documented the adverse effects on aggregate output growth, total factor and labor productivity, fiscal sustainability, and knowledge creation; another emphasizes endogenous adjustments — delayed retirement, human capital investment, and robotics adoption — that can partially offset the adverse impacts of aging. Both strands focus almost exclusively on national or cross-country outcomes, leaving open the question of how aging reshapes the spatial distribution of economic activity *within* countries. Existing theoretical frameworks predict that aging acts as an agglomerative force through demand-linked capital accumulation in the presence of capital mobility frictions: aging leads to a rise in local consumption, income, savings and increased local investment, reinforcing agglomeration and lifting productivity and rental premia. Causal evidence on these channels — particularly in developing economies, where capital mobility frictions are likely more pronounced — remains scarce.

This paper studies demographic patterns in Thailand, a middle-income economy undergoing one of the fastest aging transitions in the developing world. The availability of individual-level panel wage data, tambon-level administrative population registers, annual consumption expenditure surveys, regular establishment censuses and administrative data on savings and loans from commercial banks upto the district level, makes Thailand an unusually rich setting to examine the within-country economic effects of

aging. We use this data to estimate the causal effect of changes in the local elderly share on sub-district (tambon) level economic outcomes using a Bartik-style shift-share instrument that interacts 1998 cohort sizes at the tambon level with Thailand's national cohort survival rates. A battery of robustness checks — alternative base years and estimators, outlier-detection tests, controls for changes in younger-age shares, and the diagnostics based on Goldsmith-Pinkham, Sorkin, and Swift (2020) — supports the validity of the research design.

We find that a one-percentage-point increase in the local elderly share raises the tambon-level labor productivity premium by approximately 2.7 percent, rental costs by approximately 2.6 percent and reduces household rental expenditure share falls by roughly 0.6 percentage points. We find limited evidence of labor scarcity driving these wage and rental premiums. Consistent with our theoretical model, we find that aging leads to higher demand for goods and services. In the presence of capital mobility frictions, our model predicts aging areas to experience higher savings and investment. Applying an IV mediation analysis based on Dippel, Gold, Heblich, and Pinto (2022), we show that aging raises local investment predominantly through a savings channel: a one-percentage-point rise in the district-level elderly share – which takes about 5 years to materialize – raises local savings by 11.5 million baht, and each additional baht of savings translates into 0.85 baht of local investment. Aging's direct effect on investment, net of savings, is negative. Firm-level census data corroborate these patterns. In tradable capital-intensive manufacturing sector, the same demographic shift raises tambon-level revenue per man-hour by 3.8 percent annually, alongside higher wage bills, rising investment rates, and greater establishment-level worker concentration — with no change in the aggregate number of workers, consistent with agglomeration rather than labor-force expansion as the operative margin. The non-tradable less capital intensive services sector experiences declines in revenue per man-hour, employment, and wage bills, and no significant agglomeration response.

Our findings have implications beyond Thailand. Where capital mobility frictions are a common feature of developing economies, the within-country agglomeration response documented here offers a margin through which labor productivity may rise and offset the negative effects of aging on labor supply. This is a qualitatively distinct adjustment channel from those emphasized in the existing literature—robotics adoption (Acemoglu and Restrepo, 2017; Acemoglu et al. 2026), delayed retirement (Maestas and Zissimopoulos, 2010), and cross-country labor mobility (Pritchett, 2026)—and opens scope for public policy to address the spatial misallocation that prevents the formation of such agglomerations.

Our paper contains three main limitations. First, identification exploits differential

changes in elderly shares across tambons within the same district and year. By construction, this absorbs any general-equilibrium effects of aging operating at the district level or above. Second, although we provide evidence in support of internal capital mobility frictions, we are unable to prove conclusively prove that the sources of such frictions given the data in hand. Third, Thailand's demographic transition — with an elderly share near 13 percent — means that it is at a stage where demand-generating effects of aging may still dominate the labor supply channel. Whether the agglomeration response documented here persists, attenuates, or reverses as Thailand approaches the demographic profile of Japan or Korea remains an open empirical question.

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A Appendix

A.1 Figures

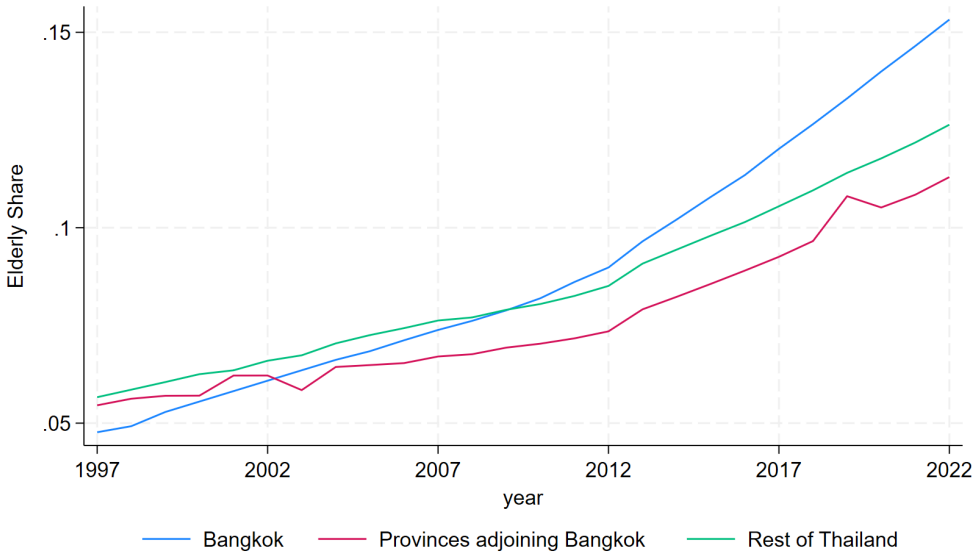


Figure A1: Aging trends in Bangkok, provinces adjoining Bangkok and the rest of the Thailand

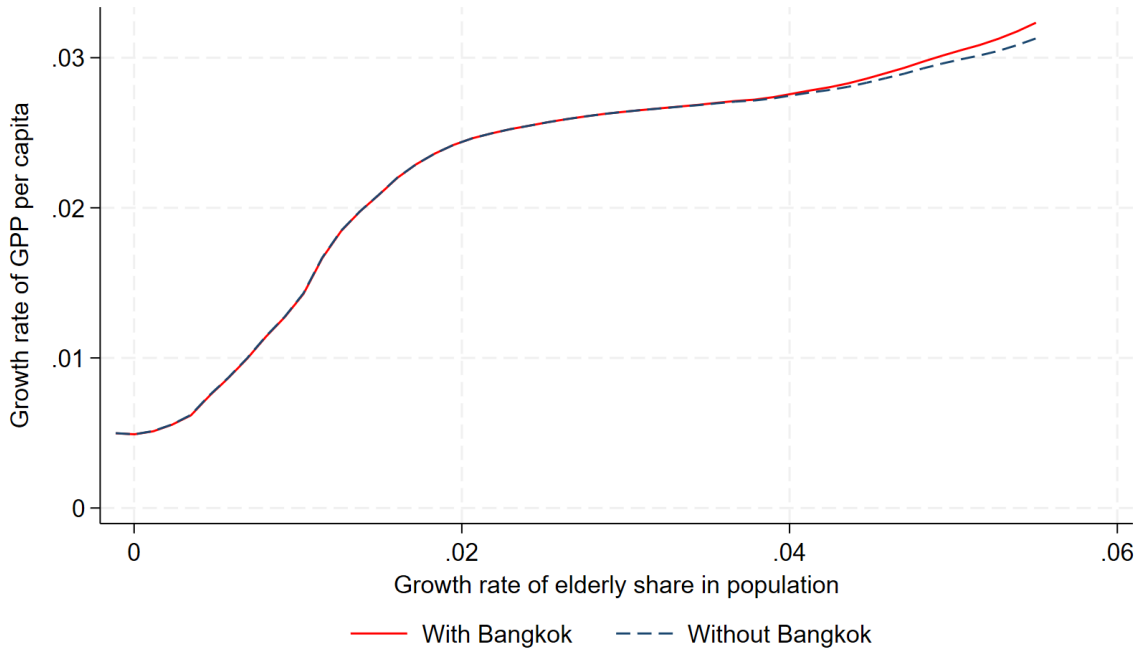


Figure A2: Growth in aging and gross provincial product (GPP)
Growth rates show cumulative annualized 10-year changes between 2004-2020. The GPP is a chained volume measure with reference year 2002, obtained from the Office of the National Economic and Social Development Council (NESDC). Demographic data is from DOPA.

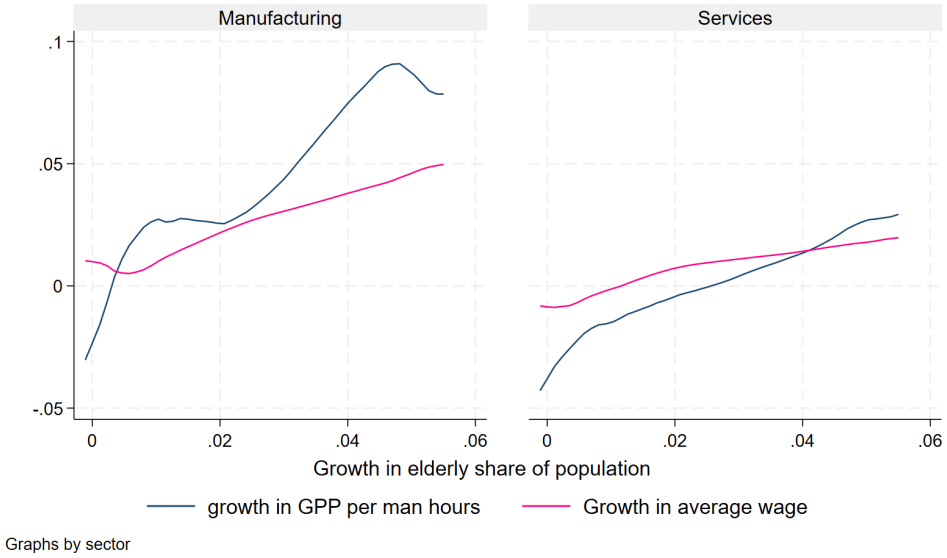


Figure A3: Changes in sectoral log wages, GPP per worker man hours and aging at the provincial level

Notes: Changes are computed over 10-year periods spanning 2004–2019. Manufacturing and services gross provincial product (GPP) are chain volume measures with reference year 2002, obtained from the National Economic and Social Development Council (NESDC). Annual worker manhours are estimated from the Labor Force Survey panel, covering all workers in manufacturing and services sectors including non-wage earners, and are aggregated to the province level using sampling weights. The average wage is the mean log wage of wage earners at the province level, constructed from the same data and sampling weights.

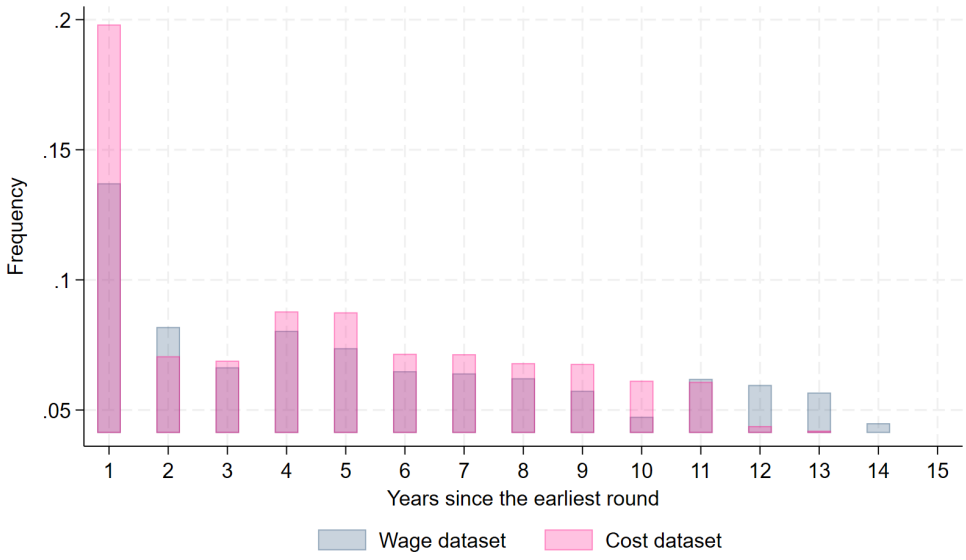


Figure A4: Distribution of year-spans in the wage and cost datasets

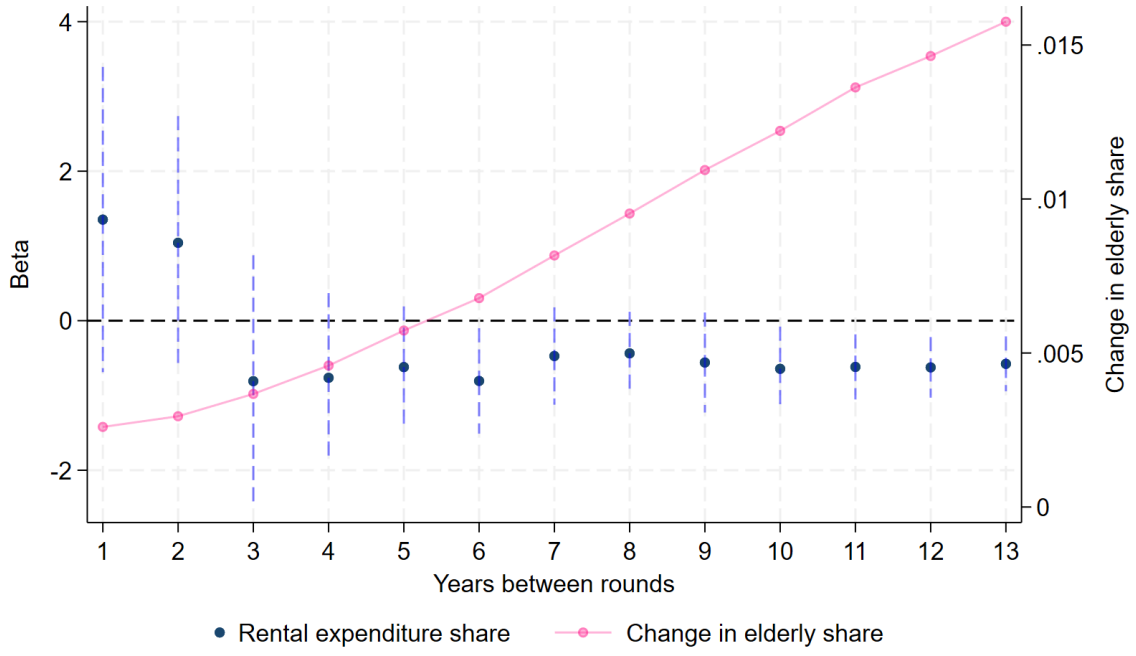


Figure A5: Impact of changes in elderly share on rental expenditure shares over time horizon

Notes: The horizontal axis denotes the maximum differencing window included in the estimation sample. At horizon h, the sample comprises all tambons reinterviewed within h years of their first appearance. The spike shows 95 percent confidence intervals based on Conley (1999) standard errors that allow for spatial and serial correlation of the error term. All specification instrument for changes in population density and include controls for changes in migration.

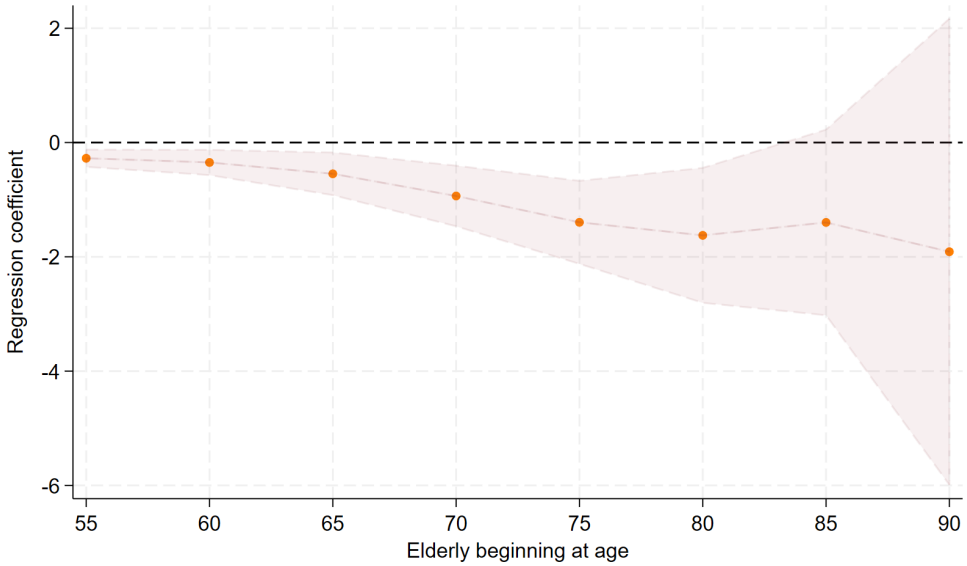
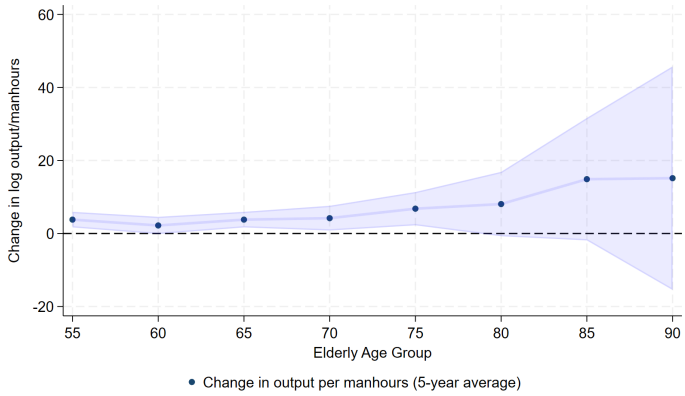
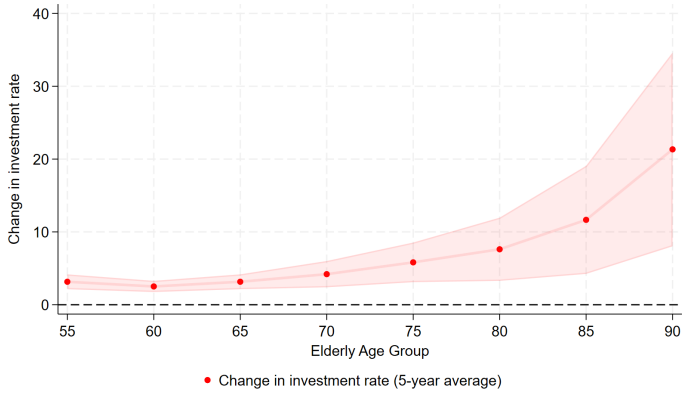


Figure A6: Effects of changes in elderly age groups on rental expenditure share

Notes: The horizontal axis shows the definition of elderly: at age h, the elderly share comprises of all ages between h to 100. The regression coefficient is on the left vertical axis while the estimated effect is on the right vertical axis. The estimated effect is the product of the regression coefficient and mean changes in elderly share. The shaded area 95 percent confidence intervals based on Conley (1999) standard errors that allow for spatial and serial correlation of the error term. All specification instrument for changes in population density and include controls for changes in migration and non-Thai population.



(a) Change in revenue per worker manhours

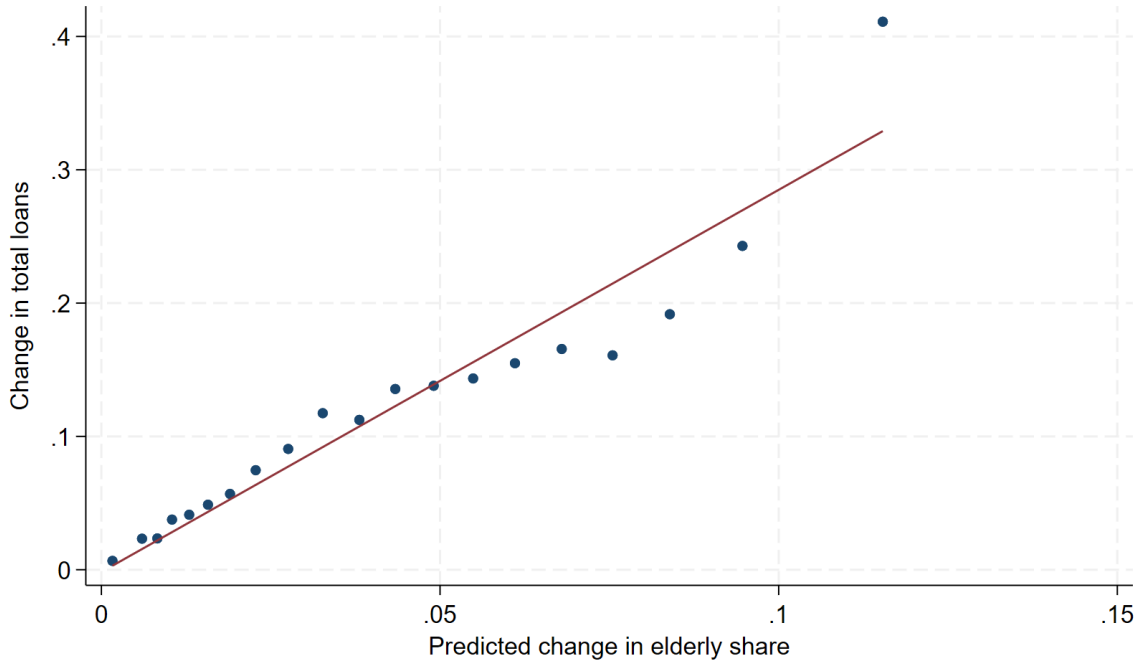


(b) Change in investment-capital rate

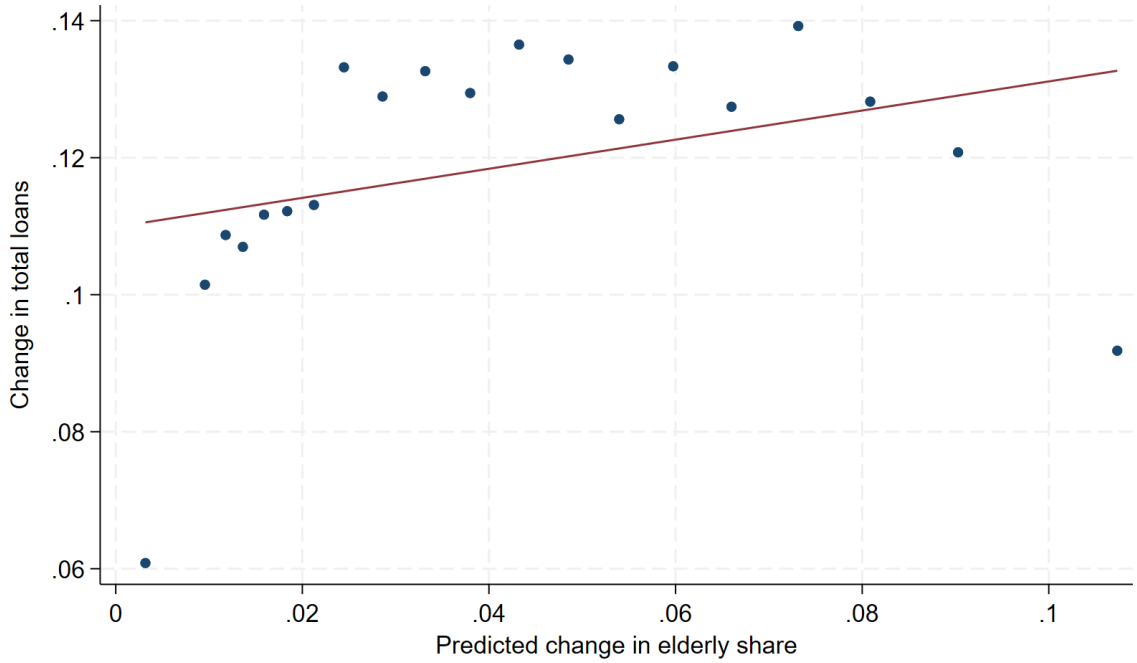


(c) Change in wagebill per worker manhours

Figure A7: Changes in manufacturing firm-outcomes by elderly age group
Notes: The horizontal axis shows the different definitions of elderly groups at 5-year intervals upto 100. Estimated coefficients are at 5-year intervals. Confidence intervals are at the 95% level with Conley (1999) standard errors that allow for spatial and serial correlation of the error term. All specification instrument for changes in population density and include controls for changes in migration and non-Thai population.



(a) Change in investment



(b) Change in investment controlling for changes in savings

Figure A8: Aging, Investments and Savings
Notes: The horizontal axis shows the predicted share of elderly based on our bartik-styled instrument using data from 1998 DOPA. The vertical axis represent changes in loan values in millions of Thai bahts. The unit of observation is district-year and changes for each variable are relative to the first year in which a district appears in the Bank of Thailand's loan and savings dataset. Each scatterplot displays 20 equally sized bins constructed using Stata's *binscatter* command.

A.2 Tables

	2004–2009	2010–2014	2015–2019
Panel A: Demographics			
Age	36.65	37.90	38.29
Male	0.55	0.55	0.54
Married	0.69	0.68	0.64
Household size	3.29	3.27	3.07
Rural	0.59	0.55	0.45
Panel B: Region			
Bangkok	0.19	0.18	0.22
Central	0.29	0.29	0.37
North	0.17	0.18	0.12
Northeast	0.22	0.23	0.16
South	0.12	0.13	0.13
Panel C: Education			
Below primary	0.24	0.18	0.11
Primary	0.20	0.19	0.17
Secondary	0.28	0.31	0.34
Above secondary	0.27	0.32	0.38
Panel D: Employment			
Industry	0.37	0.29	0.36
Services	0.47	0.37	0.57
Weekly hours	45.90	45.77	44.40
Wages (baht/day)	55.36	66.54	90.04
Log wages	3.53	3.79	4.20
Observations	701,625	397,697	549,363
Unique tambons	3,939	3,646	3,844

Table A1: Summary statistics from LFS worker panel dataset
Notes: Sample includes wage and salaried workers with non-zero reported wages from the Thai Labor Force Survey (LFS), 2004–2019. Columns report period means. Wages are in Thai baht per day. Observations are totals across all surveys within a period; unique tambons are the maximum number of tambons in any year within a period; all other observations are means across all period within the year.

	2006–2010	2011–2015	2015–2019
Panel A: Housing characteristics			
Owner-occupied	0.81	0.80	0.77
Rooms	2.69	2.74	2.75
Bedrooms	1.77	1.80	1.79
Electricity	0.99	0.99	1.00
Detached/townhouse	0.96	0.95	0.95
Apartment/condo	0.02	0.04	0.04
Panel B: Rental costs and expenditure			
Log rent	7.25	7.51	7.67
Housing expenditure share	0.16	0.14	0.17
Log monthly per capita expenditure	8.17	8.66	8.68
Observations	212,471	209,127	170,668

Table A2: Summary Statistics: Socio-Economic Survey, 2006–2019
Notes: Sample drawn from Thailand's Socio-Economic Survey (SES). Columns report period means. Rent includes both actual payments by tenants and imputed values reported by owner-occupiers. Housing expenditure share is the ratio of rent to total household consumption expenditure. All monetary values are in Thai baht.

Year	Log revenue	Log capital	Log selling expenses	Firms	Workers
Panel A: Manufacturing					
2012	14.44	14.29	11.82	13.45	29.22
2017	14.64	14.52	11.85	15.70	31.34
2022	15.25	15.23	12.53	10.39	29.61
Panel B: Services					
2012	14.65	14.25	—	15.85	8.58
2022	15.23	14.96	—	13.39	10.96

Table A3: Summary Statistics: Manufacturing and Services Censuses
Notes: Sample includes all enumerated establishments from Thailand's manufacturing censuses (2012, 2017, 2022) and services censuses (2012, 2022). All variables at collapsed at the tambon-year level. Average revenue, capital, and selling expenses per tambon are reported in logs of Thai baht. Workers and firms are the average number of employees and establishment per tambon. Selling expenses are not available in the services census.

	(1) Loans	(2) Loans	(3) Loans	(4) Loans	(5) Loans	(6) Loans	(7) Loans	(8) Δ_{10} Loans	(9) Δ_{10} Loans
Deposit	0.582***	0.513***	0.513***	0.513***	0.513***	0.513***	0.720***		
	(0.071)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.240)		
Deposit - Lag 1 year		0.253***	0.254***	0.253***	0.252***	0.253***	-0.326		
		(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.356)		
Deposit - Lag 2 year			-0.301***	0.029	0.044	0.034	0.258		
			(0.030)	(0.293)	(0.301)	(0.311)	(0.531)		
Deposit - Lag 3 year				-0.366	-0.157	-0.146	0.512		
				(0.318)	(0.478)	(0.503)	(0.702)		
Deposit - Lag 4 year					-0.250	0.059	-1.126*		
					(0.312)	(0.447)	(0.609)		
Deposit - Lag 5 year						-0.345	0.765**		
						(0.255)	(0.325)		
Δ_{10} Deposit								0.582***	0.643***
								(0.071)	(0.035)
Constant	-7.018	-0.945***	0.291***	0.348***	0.383***	0.435***	0.087***	-17.929	0.168***
	(4.419)	(0.077)	(0.092)	(0.095)	(0.102)	(0.101)	(0.030)	(11.261)	(0.022)
N	4625	4302	3984	3681	3387	3100	2473	1807	1429

Table A4: Frictions in internal capital mobility

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns (1) to (6) regresses loans per capita on savings per capita across districts in Thailand, controlling for lagged deposits per capita at one year increments, replicating the analysis of Feldstein and Horioka 1980 to detect frictions in international capital mobility. Column (7) excludes districts from Bangkok. Column (8) runs the same specification using 10 year differences in both variables; in Column (9) districts from Bangkok province are excluded.

	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
$\Delta \frac{E_{c,t}}{N_{c,t}}$	0.008	-0.458**	-0.577***	-0.605***	-0.612**	-.593**
	(0.029)	(0.180)	(0.187)	(0.192)	(0.243)	(0.188)
$\Delta n_{c,t}$	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai			0.002**	0.002**	0.002**	0.002**
			(0.001)	(0.001)	(0.001)	(0.001)
Δ log migrant			-0.002**	-0.002**	-0.002**	-0.002 **
			(0.001)	(0.001)	(0.001)	(0.001)
Food Beverages				0.000	0.000	
				(0.000)	(0.000)	
Health				-0.000	-0.000	
				(0.000)	(0.000)	
Hotels				-0.000	-0.000	
				(0.000)	(0.000)	
Retail				-0.000	-0.000	
				(0.000)	(0.000)	
Transport				0.000	0.000	
				(0.000)	(0.000)	
ΔNTL						0.000
						(0.000)
Constant	0.000	-0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	19742	19409	19409	19409	19409	19409
F-statistic	.	557.291	334.060	351.704	366.142	278.750
District X Year FE	✓	✓	✓	✓	✓	✓

Table A5: Impact of elderly shares on rental expenditure share
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\frac{E_{c,t}}{N_{c,t}}$ indicates the share of elderly population within tambon and $\Delta n_{c,t}$ change in population density. Column (5) supplements the specification in (4) by tambon latitude and longitude interacted with year. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outliers related to:							
	$\Delta\frac{E_{c,t}}{N_{c,t}}$	$\Delta\frac{\hat{E}_{c,t}}{\hat{N}_{c,t}}$	$\hat{Z}_{c,t}$	$\Delta n_{c,t}$	$\Delta\hat{n}_{c,t}$	Δ log NT	Δ log M	All
$\Delta\frac{E_{c,t}}{N_{c,t}}$	2.638**	3.408***	1.363***	1.734*	1.835*	2.530**	2.450**	0.776
	(1.161)	(1.216)	(0.422)	(1.039)	(1.018)	(1.006)	(1.076)	(0.720)
$\Delta n_{c,t}$	-0.000	-0.000	0.000	0.001	0.001*	0.000	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai	-0.007	-0.010	-0.004	-0.008	-0.002	-0.008	-0.003	0.005
	(0.007)	(0.007)	(0.003)	(0.007)	(0.006)	(0.009)	(0.007)	(0.006)
Δ log migrant	0.018**	0.020**	0.006	0.012*	0.013	0.017**	0.017**	-0.001
	(0.008)	(0.008)	(0.004)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
Constant	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
N	24605	24654	24519	25096	24803	24840	24612	12694
F-statistic	8.463	61.485	489.577	99.237	72.201	468.247	485.069	60.5
District X Year FE	✓	✓	✓	✓	✓	✓	✓	✓
mean $\Delta\frac{E_{c,t}}{N_{c,t}}$	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.018

Table A6: Sensitivity to outliers: Impact on productivity premium

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column applies a different outlier exclusion criterion: columns (1) through (7) sequentially drop observations below the 5th or above the 95th percentile—computed within each year span—of changes in the elderly share, predicted elderly share, productivity premium, population density, predicted population density, log non-Thai population (NT), and log migrants (M), respectively. Column (8) excludes outliers along all seven dimensions jointly. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outliers related to:							
	$\Delta\frac{E_{c,t}}{N_{c,t}}$	$\Delta\frac{\hat{E}_{c,t}}{\hat{N}_{c,t}}$	$\hat{\psi}^{cost}_{c,t}$	$\Delta n_{c,t}$	$\Delta\hat{n}_{c,t}$	Δ log NT	Δ log M	All
$\Delta\frac{E_{c,t}}{N_{c,t}}$	2.467**	2.686**	3.728***	1.673	2.250**	2.884***	2.705***	2.372**
	(1.026)	(1.120)	(0.665)	(1.060)	(1.065)	(1.120)	(1.013)	(1.003)
$\Delta n_{c,t}$	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Δ log non-thai	0.007	0.004	0.003	0.008	0.006	0.005	0.005	0.008
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.009)	(0.007)	(0.009)
Δ log migrant	-0.016***	-0.010	-0.007	-0.021***	-0.016***	-0.012**	-0.014	-0.027**
	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.006)	(0.009)	(0.012)
Constant	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	17005	17003	16882	17387	17165	17096	16957	8614
F-statistic	7.996	99.207	246.201	47.674	55.047	210.113	260.481	34.227
District X Year FE	✓	✓	✓	✓	✓	✓	✓	✓
mean $\Delta\frac{E_{c,t}}{N_{c,t}}$	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016

Table A7: Sensitivity to outliers: Impact on rental costs
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column applies a different outlier exclusion criterion: columns (1) through (7) sequentially drop observations below the 5th or above the 95th percentile—computed within each year span—of changes in the elderly share, predicted elderly share, rental cost, population density, predicted population density, log non-Thai population (NT), and log migrants (M), respectively. Column (8) excludes outliers along all seven dimensions jointly. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outliers related to:							
	$\Delta\frac{E_{c,t}}{N_{c,t}}$	$\Delta\frac{\hat{E}_{c,t}}{\hat{N}_{c,t}}$	$\hat{\psi}^{share}_{c,t}$	$\Delta n_{c,t}$	$\Delta\hat{n}_{c,t}$	Δ log NT	Δ log M	All
$\Delta\frac{E_{c,t}}{N_{c,t}}$	-0.573***	-0.691***	-0.502***	-0.650***	-0.548***	-0.532**	-0.531***	-0.726***
	(0.188)	(0.197)	(0.134)	(0.208)	(0.198)	(0.212)	(0.198)	(0.169)
$\Delta n_{c,t}$	0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai	0.001	0.002*	0.002**	0.003**	0.003**	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Δ log migrant	-0.002**	-0.002**	-0.001	-0.002**	-0.002*	-0.002**	-0.002	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Constant	0.000	0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	17005	17003	16882	17387	17165	17096	16957	8614
F-statistic	7.996	99.207	246.201	47.674	55.047	210.113	260.481	34.227
District X Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Table A8: Sensitivity to outliers: Impact on rental expenditure share
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column applies a different outlier exclusion criterion: columns (1) through (7) sequentially drop observations below the 5th or above the 95th percentile—computed within each year span—of changes in the elderly share, predicted elderly share, rental share in household expenditure, population density, predicted population density, log non-Thai population (NT), and log migrants (M), respectively. Column (8) excludes outliers along all seven dimensions jointly. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1) $\Delta\hat{Z}_{c,t}$	(2) $\Delta\hat{\psi}^{cost}_{c,t}$	(3) $\Delta\hat{\psi}^{share}_{c,t}$
$\Delta \log \frac{E_{c,t}}{N_{c,t}}$	0.137**	0.195***	-0.046***
	(0.066)	(0.074)	(0.014)
$\Delta n_{c,t}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
$\Delta \log$ non-thai	-0.008	0.006	0.002
	(0.006)	(0.006)	(0.001)
$\Delta \log$ migrant	0.011*	-0.017***	-0.002**
	(0.007)	(0.006)	(0.001)
Constant	0.000	0.000	-0.000
	(0.003)	(0.002)	(0.000)
N	27922	19380	19380
F-statistic	11.259	7.424	7.424
District X Year FE	✓	✓	✓

Table A9: Elasticity: log-log specification
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The model headings note the dependant variable: $\Delta\hat{Z}_{c,t}$ = changes in log productivity; $\Delta\hat{\psi}^{cost}_{c,t}$: changes in log rental costs; $\Delta\hat{\psi}^{share}_{c,t}$: changes in rental expenditure share. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1) $\Delta\hat{Z}_{c,t}$	(2) $\Delta\hat{Z}_{c,t}$	(3) $\Delta\hat{\psi}^{cost}_{c,t}$	(4) $\Delta\hat{\psi}^{cost}_{c,t}$	(5) $\Delta\hat{\psi}^{share}_{c,t}$	(6) $\Delta\hat{\psi}^{share}_{c,t}$
$\Delta \frac{E_{c,t}}{N_{c,t}}$	2.655**	2.655**	2.591*	2.591**	-0.577***	-0.577***
	(1.238)	(1.306)	(1.326)	(1.018)	(0.211)	(0.169)
$\Delta n_{c,t}$	0.000	0.000	0.000	0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta \log$ non-thai	-0.008	-0.008	0.006	0.006	0.002	0.002
	(0.010)	(0.010)	(0.008)	(0.009)	(0.002)	(0.001)
$\Delta \log$ migrant	0.016	0.016	-0.015*	-0.015*	-0.002*	-0.002
	(0.011)	(0.012)	(0.009)	(0.008)	(0.001)	(0.001)
N	27962	27962	19409	19409	19409	19409
F-statistic	300.904	146.853	145.355	118.347	145.355	118.347
District X Year FE	✓	✓	✓	✓	✓	✓

Table A10: Clustered Standard Errors
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Model headings denote the dependent variable in each specification: $\Delta\hat{Z}_{c,t}$ = changes in log productivity; $\Delta\hat{\psi}^{cost}_{c,t}$= changes in log rental costs; $\Delta\hat{\psi}^{share}_{c,t}$= changes in rental expenditure share. Changes in density are instrumented simultaneously using predicted population from 1998 DOPA data. Columns (1),(3) and (5) are clustered at the province level; the rest are clustered at the district level.

	(1) Bartik	(2) 2SLS	(3) CUE	(4) MFUL
Panel A: Productivity Premium				
$\Delta\frac{E_{c,t}}{N_{c,t}}$	2.655**	2.580*	2.263*	2.632***
	(1.306)	(1.443)	(1.352)	(0.541)
N	27962	27962	27962	27962
Test statistic	.	10.330	10.343	49.900
Test statistic (p-value)	.	0.111	0.111	0.000
District X Year FE	✓	✓	✓	✓
Panel B: Rental Cost				
$\Delta\frac{E_{c,t}}{N_{c,t}}$	2.591**	2.543**	2.690***	2.612***
	(1.018)	(0.994)	(0.980)	(0.499)
N	19409	19409	19409	19409
Test statistic		11.790	11.799	50.182
Test statistic (p-value)		0.067	0.067	0.000
District X Year FE	✓	✓	✓	✓
Panel C: Rental Expenditure Share				
$\Delta\frac{E_{c,t}}{N_{c,t}}$	-0.577***	-0.478***	-0.524***	-0.500***
	(0.169)	(0.164)	(0.162)	(0.081)
N	19409	19409	19409	19409
Test statistic		7.655	7.592	53.069
Test statistic (p-value)		0.264	0.270	0.000
District X Year FE	✓	✓	✓	✓

Table A11: Alternate estimators and over-identification tests

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "Bartik" indicates the just identified specification clustered at the district level. "2SLS" is the over-identified IV specification with cohort sizes of 65–69, 70–74, 75–79, 80–84, 85–89, 90–94, and 95–100 in the 1998 population, multiplied by cohort-survival rate across Thailand serving as multiple instruments. The overidentification test statistic for this estimator is Hansen-J due to heteroskedastic standard errors. "CUE" is the continuously-updated GMM estimator of Hansen, Heaton, and Yaron (1996) with Hansen-J statistic use for the overidentification test. Standard errors are clustered at the district level. "MFUL" is the Heteroskedasticity-Robust Fuller estimator of Hausman et al. (2012) with overidentification test from Chao et al. (2014). District-year fixed effects are partialled out of all variables before running the MFUL estimator. All estimators simultaneously instrument for changes in population density and control for log migration and log non-Thai population changes.

	(1)	(2)	(3)	(4)	(5)
$\Delta\frac{E_{c,t}}{N_{c,t}}$	2.661***	3.002**	2.896**	2.662**	2.587**
	(1.019)	(1.176)	(1.220)	(1.224)	(1.237)
$\Delta\frac{E_{30-55,c,t}}{N_{c,t}}$	-0.025				
	(0.514)				
$\Delta\frac{E_{35-55,c,t}}{N_{c,t}}$		-0.491			
		(0.488)			
$\Delta\frac{E_{40-55,c,t}}{N_{c,t}}$			-0.231		
			(0.413)		
$\Delta\frac{E_{45-55,c,t}}{N_{c,t}}$				-0.007	
				(0.457)	
$\Delta\frac{E_{50-55,c,t}}{N_{c,t}}$					0.108
					(0.725)
$\Delta n_{c,t}$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai	-0.008	-0.008	-0.008	-0.008	-0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Δ log migrant	0.016**	0.017**	0.016**	0.016**	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
N	27962	27962	27962	27962	27962
F-statistic	127.025	75.461	102.475	144.309	127.557
District × Year FE	✓	✓	✓	✓	✓

Table A12: Sensitivity of productivity premium to inclusion of younger-age groups

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is $\Delta\hat{Z}_{c,t}$ = changes in log productivity. The main variable of interest is changes in elderly share – ages 65 to 100 ($\Delta\frac{E_{c,t}}{N_{c,t}}$). Variable $\Delta\frac{E_{a-b,c,t}}{N_{c,t}}$ indicates changes in share of population ages between b and a. The specification is estimated by simultaneously instrumenting elderly population shares, changes in population share of younger age groups and changes in population density. Changes in migrants and non-Thai population enter as controls. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1)	(2)	(3)	(4)	(5)
$\Delta \frac{E_{c,t}}{N_{c,t}}$	2.532**	1.423	1.161	1.546	1.752
	(1.060)	(1.270)	(1.228)	(1.263)	(1.237)
$\Delta \frac{E_{30-55,c,t}}{N_{c,t}}$	1.652***				
	(0.639)				
$\Delta \frac{E_{35-55,c,t}}{N_{c,t}}$		2.340***			
		(0.644)			
$\Delta \frac{E_{40-55,c,t}}{N_{c,t}}$			1.624***		
			(0.438)		
$\Delta \frac{E_{45-55,c,t}}{N_{c,t}}$				1.140**	
				(0.476)	
$\Delta \frac{E_{50-55,c,t}}{N_{c,t}}$					1.378*
					(0.781)
$\Delta n_{c,t}$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai	0.005	0.004	0.006	0.006	0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Δ log migrant	-0.016***	-0.016***	-0.015***	-0.014**	-0.015***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
N	19409	19409	19409	19409	19409
F-statistic	84.147	32.275	37.643	58.598	54.087
District × Year FE	✓	✓	✓	✓	✓

Table A13: Sensitivity of rental costs to inclusion of younger-age groups
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is $\Delta \hat{\psi}_{c,t}^{cost}$ = changes in log rental costs. The main variable of interest is changes in elderly share – ages 65 to 100 ($\Delta \frac{E_{c,t}}{N_{c,t}}$). Variable $\Delta \frac{E_{a-b,c,t}}{N_{c,t}}$ indicates changes in share of population ages between b and a. The specification is estimated by simultaneously instrumenting elderly population shares, changes in population share of younger age groups and changes in population density. Changes in migrants and non-Thai population enter as controls. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1)	(2)	(3)	(4)	(5)
$\Delta \frac{E_{c,t}}{N_{c,t}}$	-0.571***	-0.600***	-0.596***	-0.491**	-0.474**
	(0.180)	(0.197)	(0.201)	(0.204)	(0.208)
$\Delta \frac{E_{30-55,c,t}}{N_{c,t}}$	-0.154*				
	(0.086)				
$\Delta \frac{E_{35-55,c,t}}{N_{c,t}}$		0.047			
		(0.089)			
$\Delta \frac{E_{40-55,c,t}}{N_{c,t}}$			0.022		
			(0.074)		
$\Delta \frac{E_{45-55,c,t}}{N_{c,t}}$				-0.093	
				(0.075)	
$\Delta \frac{E_{50-55,c,t}}{N_{c,t}}$					-0.168
					(0.119)
$\Delta n_{c,t}$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ log non-thai	0.003**	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δ log migrant	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	19409	19409	19409	19409	19409
F-statistic	84.147	32.275	37.643	58.598	54.087
District × Year FE	✓	✓	✓	✓	✓

Table A14: Sensitivity of rental expenditure share to inclusion of younger-age groups

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is $\Delta\hat{\psi}_{c,t}^{share}$ = changes in share of rental costs. The main variable of interest is changes in elderly share – ages 65 to 100 ($\Delta \frac{E_{c,t}}{N_{c,t}}$). Variable $\Delta \frac{E_{a-b,c,t}}{N_{c,t}}$ indicates changes in share of population ages between b and a. The specification is estimated by simultaneously instrumenting elderly population shares, changes in population share of younger age groups and changes in population density. Changes in migrants and non-Thai population enter as controls. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1) $\Delta\hat{Z}_{c,t}$	(2) $\Delta\hat{\psi}^{cost}_{c,t}$	(3) $\Delta\hat{\psi}^{share}_{c,t}$
$\Delta\frac{E_{c,t}}{N_{c,t}}$	2.269**	4.982***	-0.571**
	(0.881)	(1.103)	(0.271)
$\Delta n_{c,t}$	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Δ log non-thai	-0.007	-0.002	0.003*
	(0.007)	(0.007)	(0.001)
Δ log migrant	0.022***	-0.002	-0.001
	(0.008)	(0.007)	(0.001)
Constant	-0.000	-0.000	0.000
	(0.003)	(0.002)	(0.000)
N	23738	19196	19196
F-statistic	4.088	7.470	7.470
District × Year FE	✓	✓	✓

Table A15: Estimates based on 1990 Population Census
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Model headings denote the dependent variable in each specification: $\Delta\hat{Z}_{c,t}$ = changes in log productivity; $\Delta\hat{\psi}^{cost}_{c,t}$= changes in log rental costs; $\Delta\hat{\psi}^{share}_{c,t}$= changes in rental expenditure share. Changes in density are instrumented simultaneously using predicted population from IPUMS 1990 census microdata. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1) Employed	(2) Out of LF	(3) Unemployed	(4) Salaried	(5) Working Hours	(6) Work More	(7) Work More Hours
$\Delta\frac{E_{c,t}}{N_{c,t}}$	-1.458***	-1.628***	-2.659	-3.195***	-1.529***	4.308	5.638
	(0.429)	(0.356)	(4.367)	(0.716)	(0.446)	(4.286)	(5.050)
$\Delta n_{c,t}$	-0.000	-0.000	0.000	-0.000	-0.000	0.004	0.006
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.006)
N	18004	17852	228	16517	17984	570	570
F-statistic	568.254	612.583	10.100	353.179	567.730	1.064	1.064
District X Year FE	✓	✓	✓	✓	✓	✓	✓

Table A16: Impact on the ratio of migrant to non-migrant labor-market indicators
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a tambon-year. Each dependent variable is the change in the ratio of the migrant to the non-migrant tambon-level total of the indicated indicator; the seven indicators are defined as in Table 4. Migrant status is recorded only in the fourth-quarter LFS rounds, restricting the sample to 2004, 2005, 2007–2009, and 2015–2019; tambon identifiers are unavailable in the intervening years. Columns (3), (6), and (7) rest on small migrant subsamples with correspondingly weak first stages and are reported for completeness only; inference should rely on the employment, non-participation, salaried, and hours columns. Both specifications instrument the elderly share and population density and include district-by-year fixed effects. Conley (1999) standard errors allow for spatial and serial correlation of the error term.

	(1) $\Delta \log \frac{Y_t}{M_t}$	(2) $\Delta \log \frac{Y_t}{M_t}$	(3) $\Delta \log \frac{Y_t}{M_t}$	(4) $\Delta \log \frac{Y_t}{M_t}$	(5) $\Delta \log \frac{Y_t}{M_t}$
$\Delta \frac{E_{c,t}}{N_{c,t}}$	22.246***	20.977***	20.723***	20.798***	20.101***
	(4.943)	(4.751)	(4.493)	(4.631)	(5.051)
$\Delta \frac{E_{30-55,c,t}}{N_{c,t}}$	8.195***				
	(1.307)				
$\Delta \frac{E_{35-55,c,t}}{N_{c,t}}$		5.633			
		(.)			
$\Delta \frac{E_{40-55,c,t}}{N_{c,t}}$			5.669***		
			(2.085)		
$\Delta \frac{E_{45-55,c,t}}{N_{c,t}}$				5.223	
				(4.052)	
$\Delta \frac{E_{50-55,c,t}}{N_{c,t}}$					4.514
					(5.825)
N	7135	7135	7135	7135	7135
District × Year FE	✓	✓	✓	✓	✓

Table A17: Impact of younger-age group controls on changes revenue per man hours ($\Delta \log \frac{Y_t}{M_t}$)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is changes in revenue per man hours ($\Delta \log \frac{Y_t}{M_t}$). Variable of interest is change in elderly share of the population – ages 65 to 100 ($\Delta \frac{E_{c,t}}{N_{c,t}}$). Sample includes manufacturing establishments from 2012, 2017 and 2022 census. $\Delta \frac{E_{a-b,c,t}}{N_{c,t}}$ indicates changes in share of population ages between b and a. All specifications simultaneously instrument for changes in population density and include controls for changes in log migrants and log non-Thai nationals. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1) $\Delta\frac{I_t}{K_{t_0}}$	(2) $\Delta\frac{I_t}{K_{t_0}}$	(3) $\Delta\frac{I_t}{K_{t_0}}$	(4) $\Delta\frac{I_t}{K_{t_0}}$	(5) $\Delta\frac{I_t}{K_{t_0}}$
$\Delta\frac{E_{c,t}}{N_{c,t}}$	17.281***	16.566***	16.390***	16.723***	16.615***
	(2.500)	(2.432)	(2.488)	(2.355)	(2.454)
$\Delta\frac{E_{30-55,c,t}}{N_{c,t}}$	3.760***				
	(0.735)				
$\Delta\frac{E_{35-55,c,t}}{N_{c,t}}$		2.210***			
		(0.732)			
$\Delta\frac{E_{40-55,c,t}}{N_{c,t}}$			1.973***		
			(0.692)		
$\Delta\frac{E_{45-55,c,t}}{N_{c,t}}$				2.709***	
				(0.548)	
$\Delta\frac{E_{50-55,c,t}}{N_{c,t}}$					3.374***
					(0.682)
N	7132	7132	7132	7132	7132
District × Year FE	✓	✓	✓	✓	✓

Table A18: Impact of younger-age group controls on changes in investment-capital rate ($\Delta\frac{I_t}{K_{t_0}}$)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is changes in investment divided by book value of fixed assets at the start of the census year ($\Delta\frac{I_t}{K_{t_0}}$). Variable of interest is change in elderly share of the population – ages 65 to 100 ($\Delta\frac{E_{c,t}}{N_{c,t}}$). Sample includes manufacturing establishments from 2012, 2017 and 2022 census. $\Delta\frac{E_{a-b,c,t}}{N_{c,t}}$ indicates changes in share of population ages between b and a. All specifications simultaneously instrument for changes in population density and include controls for changes in log migrants and log non-Thai nationals. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

	(1) $\Delta\frac{W_t}{M_t}$	(2) $\Delta\frac{W_t}{M_t}$	(3) $\Delta\frac{W_t}{M_t}$	(4) $\Delta\frac{W_t}{M_t}$	(5) $\Delta\frac{W_t}{M_t}$
$\Delta\frac{E_{c,t}}{N_{c,t}}$	9.943***	10.514***	10.839***	11.475***	11.878***
	(3.496)	(3.155)	(3.393)	(3.172)	(2.266)
$\Delta\frac{E_{30-55,c,t}}{N_{c,t}}$	-2.548				
	(1.590)				
$\Delta\frac{E_{35-55,c,t}}{N_{c,t}}$		-1.360			
		(.)			
$\Delta\frac{E_{40-55,c,t}}{N_{c,t}}$			-0.630		
			(0.702)		
$\Delta\frac{E_{45-55,c,t}}{N_{c,t}}$				0.903	
				(1.630)	
$\Delta\frac{E_{50-55,c,t}}{N_{c,t}}$					2.659
					(2.534)
N	6077	6077	6077	6077	6077
District × Year FE	✓	✓	✓	✓	✓

Table A19: Impact of younger-age group controls on changes in wage bill per workers ($\Delta \log \frac{W_t}{M_t}$)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is changes in wage bill per worker man hours ($\Delta \log \frac{W_t}{M_t}$). Variable of interest is change in elderly share of the population – ages 65 to 100 ($\Delta\frac{E_{c,t}}{N_{c,t}}$). Sample includes manufacturing establishments from 2012, 2017 and 2022 census. $\Delta\frac{E_{a-b,c,t}}{N_{c,t}}$ indicates changes in share of population ages between b and a. All specifications simultaneously instrument for changes in population density and include controls for changes in log migrants and log non-Thai nationals. Conley (1999) standard errors that allow for spatial and serial correlation of the error term.

B Data Appendix

B.1 Constructing worker panels based on LFS

We identify individuals across LFS rounds using a deterministic matching algorithm based on a composite key of individual and geographic attributes: the individual identifier, relationship to the household head, gender, age, area type, province (*changwat*), district (*amphoe*), sub-district (*tambon*), enumeration block or village code, education level, and marital status. For each base quarter, we attempt a one-to-one merge against every subsequent quarter within the rotation window—both within the same calendar year and into the following year, reflecting the "2-2-2" design—retaining only observations that match uniquely on the full set of attributes.

With the exception of age, none of these characteristics are likely to change between quarters within a rotation cycle. Because age is recorded as an integer and may increase between interviews, a single merge on exact age would fail to link individuals whose birthdays fall between rounds. We address this by performing three sequential merge passes for each quarter pair: first at the reported age, then at age minus one, and finally at age plus one. An individual is considered matched if any of the three passes yields a unique link.

We repeat this procedure for each two-year rotation cycle between 2004 to 2019, starting from the first quarter of each base year through the fourth quarter of the following year, at which point the household exits the panel under the "2-2-2" structure. The matched observations are appended across all cycles to form the final worker-level panel, which we verify to be unique at the individual–quarter–year level.

Appendix Table B1 summarizes the resulting sample. The raw LFS contains between 300,000 and 530,000 unique individuals per year. Our deterministic matching algorithm links approximately 50% of these individuals across rounds, with match rates improving in later years. Restricting the panel to salaried and wage earners yields roughly 60,000 to 70,000 unique workers per year, representing 15 to 25% of the original sample.

	(1) LFS, raw	(2) Panel, all	(3) Share(%)	(4) Panel, non-zero wage earners	(5) Share(%)
2004	456,950	157,920	35	56,918	12
2005	304,193	165,750	54	67,660	22
2006	456,917	199,891	44	72,282	16
2007	318,204	183,029	58	74,068	23
2008	468,907	203,130	43	72,178	15
2009	314,235	184,372	59	74,472	24
2010	456,053	178,918	39	61,290	13
2011	531,043	157,078	30	56,845	11
2012	551,583	249,752	45	76,656	14
2013	524,000	256,842	49	75,316	14
2014	500,014	247,315	49	33,404	7
2015	481,016	251,287	52	63,351	13
2016	479,248	258,487	54	71,749	15
2017	477,170	251,142	53	68,900	14
2018	477,534	247,846	52	66,711	14
2019	457,253	249,383	55	67,276	15

Table B1: LFS sample sizes: raw, worker level panel and excluding non-zero wage earners