(2021) 51, 129–160

The Review of Regional Studies

The Official Journal of the Southern Regional Science Association

How Does the Age Structure Affect Local Economies in the US?*

Xiaochen Zhang

Duke Kunshan University, China

Abstract: This study examines the impacts of population aging on a wide range of economic indicators from a regional perspective. Many countries, including the United States, are experiencing demographic aging. This may have a dramatic impact on both the national and sub-national economies. However, there is little consensus about its impact on local sub-national economies. This study uses regional variation in age structure to explain economic outcomes at the metropolitan statistical areas (MSAs) level. In order to identify causal effects, Mahalanobis distances were calculated to identify the matched cities as instrumental variables. The study finds that regions with older age structures tend to have higher growth rates of GDP per capita and lower growth rates of unemployment, but such positive effects are likely to fade away in the long run. Additionally, there is no significant impact of age composition on income. The choice of variables is critical as it can lead to mixed results. The results are robust before, during and after the economic recession. Quantile regression is also used to explore potential heterogeneous effects among MSAs. The results show that MSAs, regardless of their size, are uniformly affected by the age structure.
Keywords: population aging, local labor market, instrumental variable, matching
JEL Codes: J11, J21, R11

1. INTRODUCTION

“With every mouth God sends a pair of hands.” This old saying provides a good starting point for thinking about the impact of population on economic growth. Demographic changes not only affect the consumption needs of an economy (the number of mouths), but also affect the productive capacity of the economy (the number of hands). Many countries are seeing their

*I am grateful to the editors, Amanda Ross and Lei Zhang, as well as anonymous reviewers for their invaluable comments and assistance. I also thank Mark Partridge, Elena Irwin, Abdoul Sam and Peter Sattler for their helpful suggestion. This paper has also benefited from comments made by the participants at 2018 Population Association of America annual conference and 2019 Southern Regional Science Association annual conference. Any remaining errors are the responsibility of the author. Xiaochen Zhang is an Assistant Professor of Applied Economics at Duke Kunshan University, Kunshan, Suzhou, Jiangsu, China. *Corresponding Author:* X. Zhang, Email: xiaochen.zhang@dukekunshan.edu.cn

ISSN 1553-0892, 0048-49X (online)
www.srsa.org/rrs

populations aging faster than before. In 2018, the population aged 65 or above outnumbered those under five years old for the first time in history. By 2050, one in six (16%) people in the world will be above 65 years old, up from one in eleven (9%) in 2019. In the US, this ratio already reached one in six in 2016 (United Nations, 2019)

As the world population grows older, there is a natural reason to worry about economic growth. With fewer people contributing to social security funds, the working-age population faces more pressure economically (Nishiyama, 2015). In addition to labor (population), other inputs, such as capital and technology, are also part of the production function, which makes the interaction of population and economic growth even more complicated (Casamatta and Batte, 2016).

The US population has experienced significant demographic changes over the last few decades. Although the sheer volume of the total population has been growing steadily over the past years, the composition of the population, including gender, race and ethnicity, has dramatically changed. These trends can be still expected to continue in the future (Ortman et al., 2014). Among all the factors contributing to this transformation, age plays a very important role. According to a Bureau of Labor Statistics report released in December 2015, the proportions of different age groups have evolved and profoundly reshaped the US labor force. In 1994, the median age of US workers was only 37.7 years, but this measure rose to 40.3 years by 2004 and to 41.9 years by 2014. This increase in the median age of the labor force can be seen across all race and gender subgroups, and also across all geographic regions. However, very little attention has been paid to this age variation at the sub-national level.

Some stylized facts about demographic changes in the US provide a starting point for this study. Although the working-age population has been growing, the growth rate has decreased. The labor force growth rate was higher than the population growth rate before 2000, but it became relatively lower thereafter (Ortman et al., 2014). The labor-force participation rate, another important aspect of labor market, has consistently declined over the years, from 66.4% in 1994 to 62.9% in 2014. However, the labor-force participation rate of the elderly population has increased concurrently (Börsch-Supan, 2003).

With a smaller working-age population, the growth of local economies could possibly decline. Therefore, the questions of interest are: how are aging Americans changing the economy? Is there any association between the aging trends and economic outcomes? This study explores the answers to these questions by examining the regional variations of such effects among metropolitan areas. To the best of my knowledge, this is the first study to examine population aging's impact on local economy at MSA level using time-differenced two-stage least square (2SLS) method.

The rest of the paper is organized as follows: in the next section, I review the methodology and findings of previous studies that assess age structure and its influence on the economy; in Section 3, I describe the data source, basic model settings and identification strategies used in the empirical analysis; regression results are discussed in Section 4; the last section is a summary of the main findings and an outlook for further research.

2. LITERATURE REVIEW

The impacts of demographic changes on the economy have been widely studied by economists. Some early economic theories focused on the growth of population (eg. the Malthusian model), under the assumption that the total resource (output) was fixed at that time. Some more recent economic theory focused less on the population growth rate (eg. the Solow model), because other factors in the production function, such as technology and physical capital, are playing a more important role today (Kelley and Schmidt, 1995). However, much of the traditional economic theories concerning economic development largely ignored the age structure. This is somewhat expected because population aging is a relatively new phenomenon, and it does not happen until the completion of demographic transition. While the increasing importance of the aging population has been well-documented (Becker et al., 1999), its economic effects have only recently come to the fore. In most literature, demographics are the main explanatory variables with economic outcomes being dependent variables. Both macro and micro data sets have been used, and a great deal of measurement has been examined in the existing research (Kelley and Schmidt, 2005).

In the field of macroeconomics, most evidences show that key macroeconomic variables will be negatively influenced by demographic structure (Aksoy et al., 2019). However, the channels through which aging affects the economy remain unclear. One line of research looks at the age effect on productivity. For example, a 5% increase in the cohort of age 40-49 over ten years seems to be associated with 1-2% productivity growth for each year in this period (Feyrer, 2007). Some research has found that the negative economic impacts of aging result from decreased saving rates, total factor productivity and investments (Kögel, 2005). Besides productivity, other economic outcomes have been examined as well. For example, it is well accepted that future developed economies will be composed of a smaller and older labor force (Prskawetz et al., 2008). The evidence further indicates that the estimated growth effects of income per capita, educational attainment and population growth would be biased if the age distribution were not accounted for.

In the field of microeconomics, the potential association between age and economic outcomes has attracted the attention of labor economists. The effects of age on earnings first captured economists' attention in the 1970s, when the peak baby-boom generation entered labor markets (Freeman, 1979). This type of research is motivated by the fact that, as the baby boom generation ages, the share of younger workers is decreasing. These researchers primarily explore the impacts of age cohort size on earnings using individual-level data (Welch, 1979).

Due to population aging, both the supply and demand sides of the economy will be affected (Maestas et al., 2013). Since equilibrium is determined by both of them, it is important to examine the offsetting impacts of an aging population.

On the supply side, the size and skill composition of labor supply will surely change. As the quantity of young labor decreases, population aging will lead to capital deepening that increases wages and productivity (Card and Lemieux, 2001; Hsu and Lo, 2019). Thus, the possible imperfect substitutability between the workforces of different ages implies that there exists an optimal age structure that leads to the maximized output (Feyrer, 2007). On the one hand, population aging, which narrows the innovative life cycle, could reduce the aggregate creative output (Jones, 2010). On the other hand, the elderly can still make a significant contribution to the economy, such as taking care of grandchildren and volunteering, although this will not be reflected in many economic statistics since these activities often do not involve monetary payments (Bloom et al., 2007). Thus, it is essential to examine the net effects on the supply side.

On the demand side, although the dissaving by the elderly can reduce the saving rates and harm the economy (Amaglobeli et al., 2019), the net impacts on consumer demand is unknown, because the age structure alters the product composition of consumer demand. For example, the elderly population could shift the demand from education to healthcare, but the net effect of these demand shifts could go either way (Assadian, 1995; Hock and Weil, 2012). Therefore, population aging can have both positive and negative impacts on both the demand and supply sides.

In summary, the relationship between age variables and economic outcomes is complicated. Although previous research has built models to explain the complicated mechanism, empirical evidence is still rare. One main reason is the challenge of dealing with the endogeneity of age structures (Prettner, 2013). Most existing empirical studies explore the age effect on the economy using either individual-level data or international comparison. However, the regional variation of age compositions within a country is largely ignored[1]. This regional approach can provide additional insights, as the confounding effect of cultural and legal differences in retirement age across national borders will not distort the results.

Drawing on the discussion above, this study aims to examine the effects of age compositions on US MSAs. To identify causal effects, the IV-matching technique is used to find suitable instrument variables. The results are robust under different specifications, and lead to the conclusion that regions with older structure tend to have relatively faster growth of GDP per capita and slower growth of unemployment, although such positive effects are likely to fade away in the long run.

3. EMPIRICAL ANALYSIS

The basic unit of analysis is the metropolitan statistical areas (MSAs) because they provide a good measure of functional economic areas. MSAs are designed explicitly by capturing local labor markets with at least 25% commuting between counties and the principal core of metro areas (Partridge et al., 2017). County-level data are not used in this study due to availability, as the Bureau of Economic Analysis only publishes GDP data at the state and MSA levels.

3.1. Explanatory Variable: Degree of Population Aging

The key variables of interest measure the relative size of the aging population in the US MSAs. Specifically, four proxies - the median age, share of prime-age (25-54 years old)

[1] There is another study examining the effects of population aging on local economy. However, only state-level data were used (Maestas et al., 2016). Compared to states, MSAs are a better measure for local labor markets in the US economy.

workers, senior dependency ratio and the share of senior population will be used to measure the age structures across MSAs.

The first explanatory variable is "median age." This is a good measure in that it can represent the age distribution of the total population. However, this measure would be less effective in evaluating labor market effects, because it is affected by the number of children who have not yet entered the labor market. The table below provides an example showing the regional variation of median ages among MSAs (only the top five and the bottom five are listed):

Table 1: MSAs with the Lowest and the Highest Median Age in 2015

MSA	Median Age
Provo-Orem, UT	24.6
Ames, IA	25.7
Logan, UT-ID	25.8
Manhattan, KS	26.3
Jacksonville, NC	26.5
...	...
National Median Age	38.0
...	...
Barnstable Town, MA	52.4
Sebring, FL	52.7
Homosassa Springs, FL	56.0
Punta Gorda, FL	57.9
The Village, FL	66.5

The second variable, "share of prime-age population," is defined as the fraction of people between 25 and 54 years old. Compared with the entire "working-age population" (defined by the U.S. Department of Labor as those between 16 and 64 years old), prime-age population has several favorable traits. One advantage is prime-age workers have not entered the retirement age window and still have strong incentives to stay in the labor force. Another advantage is that the prime-age population tends to earn more, because most high school and college students are excluded. This is a good measure of "population dividend," as it represents the most productive age group.

The third variable "the share of old population" is defined as the fraction of people above 65 years old. One advantage of this operational definition is the consistency with the concept of "population aging" as defined by OECD[2]. Another advantage is that this operational definition can largely represent the pensionable population. Social security's full-benefit retirement age is gradually increasing because of legislation passed by Congress in 1983. Based on the legislation, most people aged 65 years or older during the study period

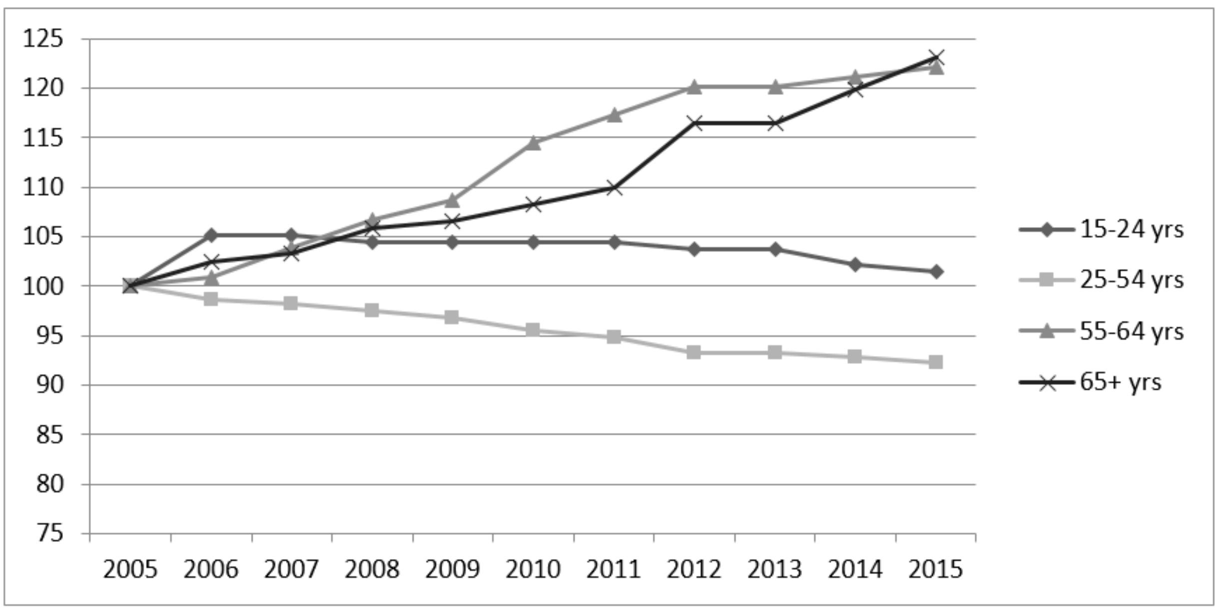
[2]https://data.oecd.org/pop/elderly-population.htm

2003-2014 would have the opportunity to retire without compromising their benefits[3]. Thus, the labor supply of this cohort was not affected by the pension concerns.

The fourth variable is the "senior dependency ratio". This ratio compares the number of people above 65 years old to the working age population. The denominator differs from the whole population in that the youth dependents are deducted from the denominator. Thus, only the economically active population are included in the calculation, which yields a more precise picture of "dependency" defined by age. The lower values may underscore greater financial pressures on the social security system.

In summary, all four proxies capture different aspects of the changing workforce and total population. Any single indicator may contain significant measurement errors which leads to estimation errors. Thus, all proxies will be examined in the following analysis in order to give a full picture of population aging's impact. The chart below displays the age composition of the US population since 2005:

Figure 1: Age Group Composition of US Population, (2005-2015)



3.2. Dependent Variable: Economic Growth, Labor Market Outcomes and Incomes

A wide range of economic indicators which evaluate different aspects of the overall economic performance is used as dependent variables. To measure the regional economic growth, I

[3]Traditionally, the full benefit age was 65, and early retirement benefits were first available at the age of 62, with a permanent reduction to 80 percent of the full benefit amount. Currently, the full-benefit retirement age in the US is 66 for people born in 1943-1954, and it will gradually rise to 67 for those born in 1960 or later.

obtained MSA-level GDP data in 2005-2015[4] from the Bureau of Economic Analysis. Both GDP per capita (the measure of well-being) and GDP per worker (the measure of productivity) were calculated. To measure labor market outcomes, I also collected indicators such as labor force participation rate, unemployment rate and the number of jobs at the MSA level from the American Community Survey and the Bureau of Economic Analysis.

The annual growth rate was calculated to measure the short-term effects, while the 10-year change rate was used to gauge the long-term effects. To account for only labor force effects, the population aged 18 or less will be excluded from the denominator when calculating per capita GDP; therefore the number of dependent children will not distort the labor market ratios. The trends of economic variables from 2005 to 2015 are displayed in Figure A.1.

3.3. Model

The basic model takes the following form:

$$\Delta Y_{i,t} = \alpha X_{i,t-1} + \beta_j + \Theta Z_{i,t-1} + \epsilon \tag{1}$$

where Y is a range of key economic indicators including GDP growth, labor market outcomes and personal incomes; ΔY represents the change rate of these economic variables in the short run (1 year) and the long run (10 years); α is the coefficient before the age structure variables, which is the main coefficient of interest; β_j is the state fixed effects, which control for time-invariant characteristics of each state; $Z_{i,t}$ is a vector of time-varying covariates including demographic factors other than age, including education, gender and race compositions of the population in one MSA in a given year. The residual is represented by ϵ, and robust standard errors are reported in the results tables.

Physical capital is also an important factor in most production functions. However, since no useful government statistics on MSA-level capital investment can be found at this time, this model assumes that the production technology, as well as the capital/labor ratio, is the same across MSAs. Therefore, the rate of return is equalized across the country. This is an appropriate assumption inside a domestic economy with highly mobile capital.

One important empirical challenge in estimating the effects is the endogeneity of the age structure. Potential confounders remain after controlling for time and state fixed effects, which could invalidate the causal relationship, since the age composition of the local population may be endogenous itself. For example, younger people are more likely to be attracted by places where there is a vital labor market with many opportunities, while places full of energetic younger people are more likely to have better economic performance. To account for these and other factors driving both the degree of population aging and the economic performance in MSAs, I use an "IV-matching" strategy to identify instrumental variables (Zhang et al., 2020). Specifically, the Mahalanobis distance will be calculated for each MSA pair to determine their best matches based on economic and demographic statistics in 2005:

[4] The American Community Survey was initially launched in 2005. The 2015 ACS data were the most recent data at the time of writing this paper.

$$d(\overrightarrow{x}, \overrightarrow{y}) = \sqrt{\sum_{i=1}^{N} \frac{(x_i - y_i)^2}{s_i^2}} \tag{2}$$

where N characteristics of MSAs will be used to calculate the distance between MSA X and MSA Y; s_i is the standard error of trait i.For example, the median age of the MSA with the smallest Mahalanobis distance will be used as an instrumental variable for the MSA of study. The calculation of Mahalanobis distance includes population size, sex ratio, share of white population and share of population with at least a Bachelor's degree. To prevent any spatial spillover effects, the matched MSA cannot be in the same state as the original MSA[5]. Since the boundaries of each MSA are based on the commuting between counties, the spatial spillover effects between nearby MSAs should not be a major issue. Descriptive statistics show that those variables chosen as criteria are highly correlated with age compositions, and their correlation is reported in Table A.2. The first stage F-statistics are also reported showing a strong association between instruments and the endogenous age structure variables.

4. RESULTS

4.1. Short-Term Effects

In this subsection, the impacts of population aging on annual changes of economic variables are examined. I begin by estimating ordinary least square (OLS) regressions to explore the relationship between age profiles and economic outcomes. The results are presented in Table A.3. From these results we can see that GDP growth rates are generally not associated with age composition. However, after controlling for the population size, MSAs with older age structures tend to have a higher growth rate of GDP per worker and GDP per capita. Regarding local labor markets, it was surprising to find that labor force participation rates are not affected by age compositions. Additionally, older age structures are likely to cause a slower growth of unemployment rates, and the results on non-farm and farm jobs are mixed. None of the four variables representing age structures was significantly associated with the growth rate of income variables.

As discussed in section 3, a matching strategy based on Mahalanobis distance was used to identify the instrumental variable for the age structures to address endogeneity. This model is the preferred approach for short-run effects, and the results are reported in Table A.4. The findings from the 2SLS models are generally consistent with those in the OLS models. First-stage F-statistics are reported and indicate no concerns about weak instruments.

[5]For example, if A is the best match for X and both of them are in the same state, then the second best match B (supposing B and X are not in the same state) will be used to instrument for X. If a MSA crosses state borders, then the state of the core metro area will be treated as the state of the MSA. For example, the state of Cincinnati-Wilmington-Maysville MSA will be Ohio, because Cincinnati is the core metro area.

4.2. Long-Term Effects

In this subsection, I examine the impacts of population aging's level on ten-year changes of economic variables. Other than short-run effects (annual growth rates), this study also looks at long-term effects (10-year change rates). The OLS results are presented in Table A.5. In the long run, MSAs with older age structures tend to have a slower GDP growth rate. However, such detrimental effects were not statistically significant after controlling for the population size. The 10-year growth of both labor-force participation rates and unemployment rates are not affected by age compositions. But the increase in median age and the share of population above 65 years old are likely to decrease total number of jobs, which is largely driven by the decrease in non-farm jobs. In terms of income measures, income per capita and mean income for full-time workers are not significantly influenced by age structures. However, increase in median age, senior dependency ratio and the proportion of elderly population is likely to reduce the 10-year growth rate of median incomes for people above 25 years old.

A matching strategy was also used to identify suitable instrumental variables, and it is the preferred model for long-run effects.[6] The results of the 2SLS model are reported in Table A.6. Based on the results, the afore-mentioned effects are all gone after instrumenting for the age structure variable, suggesting that the short-term impacts of age compositions on local economy are likely to fade away in the long run.

4.3. Time-Differenced Effects

In this subsection, the time-differenced OLS and 2SLS regressions of the following form are estimated:

$$\Delta Y_{i,t} = \alpha \Delta X_{i,t-1} + \beta_j + \Theta Z_{i,t-1} + \epsilon \tag{3}$$

where ΔX includes the change rate of age structure in both short-term (1-year) and long-term (10-year). The motivation is that some MSAs may have extremely young or old age structures, which could affect their long-run performance. If that is the case, then simply using the level of population aging would not fully capture the effect. Furthermore, time-differenced regressions will remove time-invariant factors that potentially affect both age compositions and economic outcomes (Rickman et. al, 2015). Notice, however, that the control variables are not time-differenced due to the possible endogeneity.

The results of the short-term and long-term time-differenced OLS models are reported in Table A.7 and Table A.8 respectively. Because the major explanatory variable are now the "rate of changes" rather than the "level," the interpretation will be different. Based on the short-term results, the MSAs that are getting older tend to have slower growth of GDP and GDP per capita. In terms of the local labor market performance, those MSAs are also more likely to experience a decline in labor-force participation rates, non-farm jobs as well

[6]Hausman tests were performed to test the null hypothesis of exogeneity. Most results confirmed the endogeneity of age structures. Although some results cannot reject the null hypothesis, it is hard to ignore the endogeneity issue documented by many previous studies (Finlay, 2006; DeGraff and Wong, 2014; Peterson, 2017; Prettner, 2013)

as total number of jobs. Although the growth rate of incomes is found to be not affected by the level of population aging, it is significantly impacted by the speed of aging. The findings show that those MSAs which are turning older will have reduced growth rates of income per capita and median income for people above 25 years old. These findings are consistent across all four indicators of age structures. The long-run OLS results are reported in Table A.8, and similar patterns are found for the time-difference models when 10-year growth rates are examined.

The results of short-term and long-term time-differenced 2SLS models are reported in Table A.9 and Table A.10 respectively. It can be seen that the portion of prime-age workers is still significant when using instrumental variables. In the short run, regions with a growing prime-age population tend to have higher growth rate of GDP per capita, labor-force participation rate and personal incomes. However, such positive effects tend to fade away in the long run, because none of the coefficients are statistically significant when examining ten-year changes.

4.4. Robustness Check

As a robustness check, the study period was divided into three groups: 2005-2007, 2007-2009 and 2009-2015. This allows testing for potential heterogeneous effects across different stages in the business cycle. It is possible that the effects specific to the Great Recession may be distorting the results. Thus, are economic consequences of population aging different before, during and after the recession? Specifically, OLS models are used to examine the impacts of age structures on local economy before, during and after economic recessions,[7] and the detailed results are reported in Table A.11, Table A.12 and Table A.13 respectively. However, the results across the business cycle were consistent with the earlier findings. There were no significantly different effects of age structures due to the business cycle.

As another robustness check, quantile regressions were used to test for potential differing effects of age compositions across MSAs with different sizes. The quantile regression approach can provide flexibility for modeling data with heterogeneous conditional distributions (Koenker and Hallock, 2001) and it allows for heterogeneous effects on outcome variables across the spectrum of all quantiles. Thus, I ran a series of quantile regressions using GDP per capita and unemployment rates as dependent variables, respectively, because these two indicators are consistently significant in most model settings. The coefficients of age compositions in short-run models are reported in Figure A.2 and Figure A.4, and the coefficients in long-run models are plotted in Figure A.3 and Figure A.5.

These graphs illustrate how the effects of age structures vary over quantiles, and how the effects at various quantiles differ from the OLS coefficients. On the plots of coefficients, it can be clearly seen that the difference in effects among quantiles is negligible. The median estimates are also very close to the OLS point estimates, lying within the confidence interval

[7] I divide the total number of years (2005-2015) into three parts: before recession (2005-2008), during recession (2008-2010) and after recession (2010-2015). The criteria for classifying the years are to match the official announcements made by NBER's Business Cycle Dating Committee. According to the latest "US Business Cycle Expansions and Contractions," the Great Recession began in the 4th quarter of 2007 and ended in June 2009 (the 2nd quarter). In total, the contraction lasted for 18 months.

of OLS estimates. Thus, the results cannot reject the equality of estimated coefficients over different quantiles.

5. CONCLUSIONS

This study examines the impacts of population aging on local economies using a wide range of variables, including ten economic outcome variables and four age structure variables. Both rate and level measures are examined using OLS and 2SLS regressions to find the most consistent results. Based on the above results, several conclusions can be drawn. First, age composition does not have significant impacts on the personal income of the locals. Second, in the short run, older age structures tend to have positive effects on the local economy, leading to a higher growth rate of GDP after controlling for population and a slower growth of unemployment rates. Thirdly, aforementioned positive effects are likely to fade away in the long run. The conclusions above also demonstrate the importance of choosing multiple indicators, as not all aspects of local economies are uniformly affected by all aspects of age structure. Lastly, MSAs, regardless of the size of the local economy, are almost uniformly affected by age compositions. Results from quantile regressions cannot reject the equality of coefficients before the age variables.

This study builds on the previous literature while making the following three main contributions. First, previous studies on population aging only provide evidence at the state level or on international comparison. This paper specifically focuses on MSA-level data, exploring the impact of demographic aging using a finer-solution level. Studying MSAs rather than states removes remote rural counties which presented a confounding factor, because rural demographics can be very different from urban areas. Second, this study uses more than one proxy for the degree of population aging and evaluates a wide spectrum of economic indicators. This captures a more complete picture of the economic dynamics of aging. Lastly, this study attempts to find new instrumental variables to address the endogeneity concern of age structure.

This study has two major implications for policy makers and academic researchers. First, this paper cautions local government that the potential impacts of demographic shifts could affect local economy. However, aging's impacts on local economy are mixed, and one-size-fits-all policy cannot address future demographic changes. Second, this paper cautions future studies about choosing the indicators for age structures and the measure for economic outcomes, because different choices of variables could lead to quite different results as shown in this study. A new economic measure that can include the non-market contribution of the elderly is also preferred.

Some meaningful questions about population aging's impacts on local economy remain to be answered. One line of research is to make out-of-sample predictions. Specifically, historical data can be employed to gauge the key coefficients, which represent the relationship between population aging and local economy. Thus, these coefficients can used to predict future economic performance. Another line of future research will focus on the decomposition of population aging, which results from both declining mortality and declining fertility. Theoretical models have demonstrated the potential differing impacts of these two factors. However, this empirical study cannot explore how the impact is decomposed by these two factors without MSA-level data on mortality and fertility. Lastly, the channels through which age affects the local economy still need to be examined. Future research can take a closer look at either demand or supply with local spending data.

REFERENCES

Aksoy, Yunus, Henrique S. Basso, Tobias Grasl, and Ron P. Smith. (2019) “Demographic Structure and Macroeconomic Trends,” *American Economic Journal: Macroeconomics*, 11(1), 193–222. http://doi.org/10.1257/mac.20170114.

Amaglobeli, Mr David, Hua Chai, Ms Era Dabla-Norris, Mr Kamil Dybczak, Mauricio Soto, and Alexander F Tieman. (2019) *The Future of Saving: The Role of Pension System Design in an Aging World*. International Monetary Fund.

Assadian, Afsaneh. (1995) “Fiscal Determinants of Migration to a Fast-Growing State: How the Aged Differ from the General Population,” *Review of Regional Studies*, 25(3), 301–315.

Becker, Gary S, Edward L. Glaeser, and Kevin M. Murphy. (1999) “Population and Economic Growth,” *American Economic Review*, 89(2), 145–149.

Bloom, David E., David Canning, Guenther Fink, and Jocelyn E. Finlay. (2007) “Does Age Structure Forecast Economic Growth?,” *International Journal of Forecasting*, 23(4), 569–585. http://doi.org/10.1016/j.ijforecast.2007.07.001.

Börsch-Supan, Axel. (2003) “Labor Market Effects of Population Aging,” *Labour*, 17, 5–44. http://doi.org/10.1111/1467-9914.17.specialissue.2.

Card, David and Thomas Lemieux. (2001) “Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis,” *The Quarterly Journal of Economics*, 116(2), 705–746. http://doi.org/10.1162/00335530151144140.

Casamatta, Georges and L. Batte. (2016) “The Political Economy of Population Aging,” *Handbook of the Economics of Population Aging*, 1st ed.(1). http://doi.org/10.1016/bs.hespa.2016.07.001.

DeGraff, Deborah S. and Rebeca Wong. (2014) “Modeling Old-Age Wealth with Endogenous Early-Life Outcomes: The Case of Mexico,” *Journal of Economics of Ageing*, 23(1), 1–7. http://doi.org/10.1016/j.jeoa.2013.11.002.

Feyrer, James. (2007) “Demographics and Productivity,” *The Review of Economics and Statistics*, pp. 100–109. http://doi.org/10.1162/rest.89.1.100.

Finlay, Jocelyn Edwina. (2006) *Endogenous Longevity and Economic Growth*. Citeseer.

Freeman, Richard B.. (1979) “The Effect of Demographic Factors on Age-Earnings Profiles,” *Journal of Human Resources*, pp. 289–318. http://doi.org/10.3386/w0316.

Hock, Heinrich and David N. Weil. (2012) “On the Dynamics of the Age Structure, Dependency and Consumption,” *Journal of Population Economics*, 25(3), 1019–1043. http://doi.org/10.1007/s00148-011-0372-x.

Hsu, Yuan-Ho and Huei-Chun Lo. (2019) “The Impacts of Population Aging on Saving, Capital Formation and Economic Growth,” *American Journal of Industrial and Business Management*, 9(12), 2231–2249. http://doi.org/10.4236/ajibm.2019.912148.

Jones, Benjamin F.. (2010) “Age and Great Invention,” *Review of Economics and Statistics*, 92(1), 1–14. http://doi.org/10.1162/rest.2009.11724.

Kögel, Tomas. (2005) “Youth Dependency and Total Factor Productivity,” *Journal of Development Economics*, 76(1), 147–173. http://doi.org/10.1016/j.jdeveco.2003.11.003.

Kelley, Allen C. and Robert M. Schmidt. (1995) “Aggregate Population and Economic Growth Correlations: The Role of the Components of Demographic Change,” *Demography*, 32(4), 543–555. http://doi.org/10.2307/2061674.

Kelley, Allen C. and Robert M. Schmidt. (2005) “Evolution of Recent Economic-

Demographic Modeling: A Synthesis," *Journal of Population Economics*, 18(2), 275–300. http://doi.org/10.1007/s00148-005-0222-9.

Koenker, Roger and Kevin F Hallock. (2001) "Quantile Regression," *Journal of economic perspectives*, 15(4), 143–156. http://doi.org/10.1257/jep.15.4.143.

Maestas, Nicole, Kathleen J Mullen, and David Powell. (2013) The Effect of Local Labor Demand Conditions on the Labor Supply Outcomes of Older Americans. RAND Working Paper Series WR-1019.

Maestas, Nicole, Kathleen J Mullen, and David Powell. (2016) The Effect of Population Aging on Economic Growth, the Labor Force and Productivity. National Bureau of Economic Research.

Nishiyama, Shinichi. (2015) "Fiscal Policy Effects in a Heterogeneous-Agent OLG Economy with an Aging Population," *Journal of Economic Dynamics and Control*, 62, 114–132. http://doi.org/10.1016/j.jedc.2015.09.007.

Ortman, Jennifer M, Victoria A Velkoff, Howard Hogan, et al.. (2014) An Aging Nation: The Older Population in the United States. US Department of Commerce, Economics and Statistics Administration.

Partridge, Mark D, Dan S Rickman, M Rose Olfert, and Ying Tan. (2017) "International Trade and Local Labor Markets: Do Foreign and Domestic Shocks affect Regions Differently?," *Journal of Economic Geography*, 17(2), 375–409. http://doi.org/10.1093/jeg/lbw006.

Peterson, E Wesley F. (2017) "The Role of Population in Economic Growth," *Sage Open*, 7(4), 2158244017736094. http://doi.org/10.1177/2158244017736094.

Prettner, Klaus. (2013) "Population Aging and Endogenous Economic Growth," *Journal of Population Economics*, 26(2), 811–834. http://doi.org/10.1007/s00148-012-0441-9.

Prskawetz, Alexia, Thomas Fent, and Ross Guest. (2008) "Workforce Aging and Labor Productivity: The Role of Supply and Demand for Labor in the G7 Countries," *Population and Development Review*, 34, 298–323.

United Nations. (2019) World Population Prospects 2019.

Welch, Finis. (1979) "Effects of Cohort Size on Earnings: The Baby Boom Babies' Financial Bust," *The Journal of Political Economy*, pp. S65–S97. http://doi.org/10.1086/260823.

Zhang, Min, Mark D Partridge, and Huasheng Song. (2020) "Amenities and the Geography of Innovation: Evidence from Chinese Cities," *The Annals of Regional Science*, pp. 1–41. http://doi.org/10.1007/s00168-020-00977-5.

APPENDIX

Table A.1: Variable Definitions and Summary Statistics

Variables	Definitions	Mean	Std.	Min	Max	Source
	Dependent Variable:					
Category: Economy						
gdp	GDP (million)	22805	50166	2265	491042	BEA
percapita	GDP per capita	40642	11847	18729	162786	BEA
perworker	GDP per worker	71672	15679	41016	204742	BEA
Category: Labor Market						
lfpr	labor force participation rate (%)	63.6	5.1	41.2	76.6	ACS
unemp	unemployment rate (%)	7.86	2.88	1.8	21	ACS
employ	employment rate (%)	58.04	5.79	34.1	74.1	ACS
jobtot	total number of jobs	276373	499717	37179	4647142	BEA
jobnf	number of non-farm jobs	271109	491618	36242	4434541	BEA
jobf	number of farm jobs	3100	3535	205	30379	BEA
Category: Income						
*med*16	median for people 16+ with earnings	26506	4246	14455	46945	ACS
*med*25	median for people 25+ with earnings	31975	4536	17408	53300	ACS
mean	mean for fulltime year-round workers	49269	7920	30213	107660	ACS
average	income per capita	39690	8455	17919	118695	BEA
	Explanatory Variable:					
medage	median age (years)	36.68	4.32	23.3	57.9	ACS
primeage	the share of prime-age workers (%)	39.61	2.64	26.5	47.3	ACS
olddepend	old-age dependency ratio (%)	22.04	6.36	8	78.6	ACS
*over*65	the share of population 65+ (%)	13.68	3.37	5.2	38.4	ACS
	Demographics as Control Variable:					
sex	sex ratio (males per 100 females)	97.15	4.56	83.8	140	ACS
edu	the share with college degree (%)	26.76	8.51	9.99	62.42	ACS
race	the share of white population (%)	80.7	11.59	46.42	97.44	ACS
pop	the total population	466335	801200	68203	7102165	ACS

Figure A.1: Changing Trends of the Age Structure and Local Economies (2005-2015)

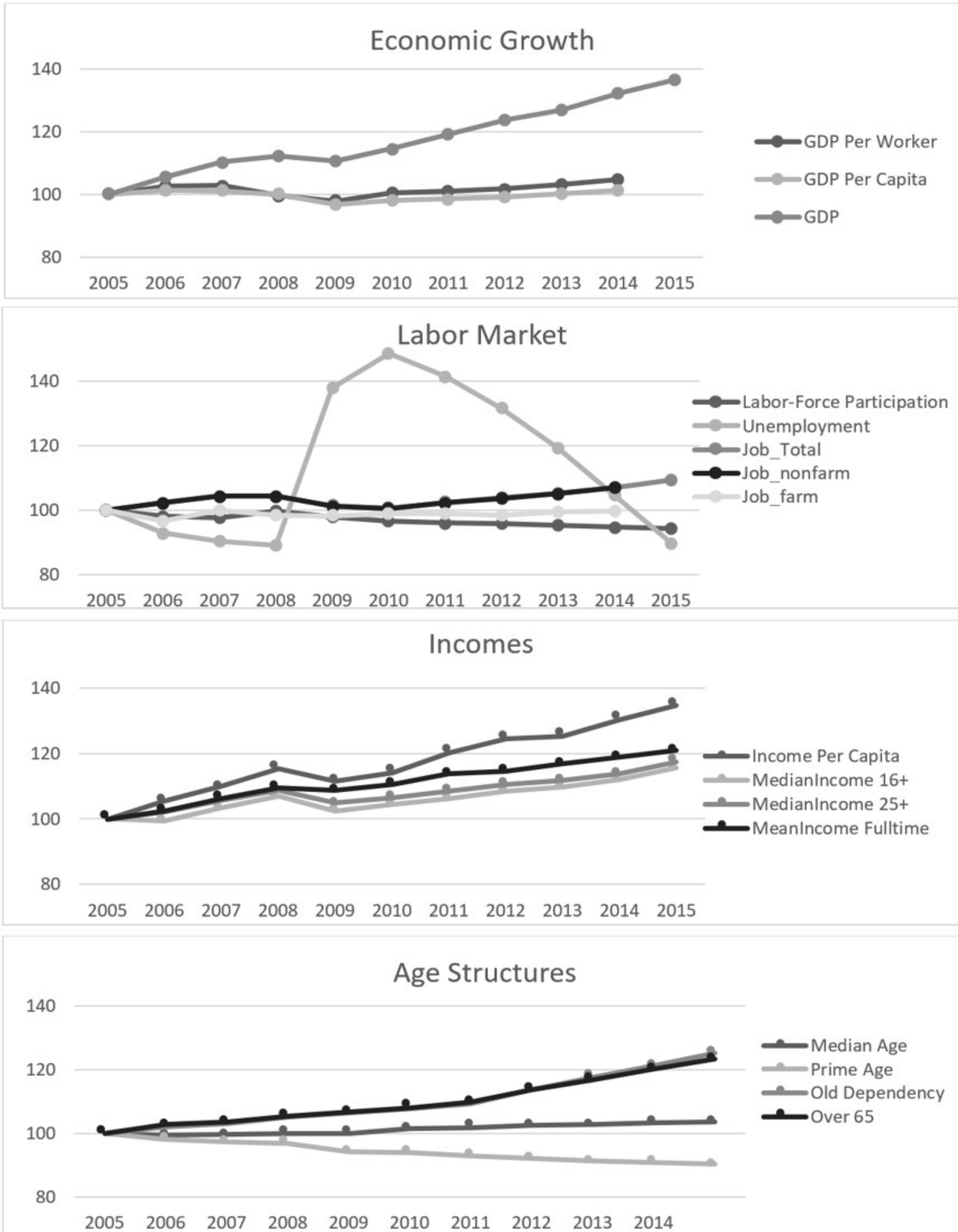


Table A.2: Criteria Used for Finding Matched MSAs (Year=2015)

	medage	**primeage**	**olddepend**	**over65**
ln(*pop*)	0.671***	0.005***	0.347	0.126
	(0.208)	(0.001)	(0.258)	(0.147)
sex	-0.536***	0.001**	-0.786***	-0.446***
	(0.073)	(0.001)	(0.122)	(0.062)
edu	-0.051*	0.001***	-0.183***	-0.073***
	(0.026)	(0.000)	(0.044)	(0.017)
race	0.158***	7×10^{-5}	0.211***	0.128***
	(0.017)	(0.000)	(0.027)	(0.014)
N	261	261	261	261
R2	0.342	0.241	0.376	0.398
Adj. R2	0.332	0.229	0.366	0.389

Note: 1. *, ** and *** indicates the coefficient is significant at 10%, 5% and 1% level respectively. 2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.

Table A.3: Results of OLS Models (Annual Growth)

	Economy			**Local Market**					**Income**			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	.001***	.008***	-.0004	-.0003	-.008***	.0005	-.0002	-.0003	-.0002	-.0004	-.0003	-.0004
Std. Err.	(.00039)	(.00029)	(.00030)	(.00023)	(.002)	(.00014)	(.00016)	(.0004)	(.00024)	(.00054)	(.00045)	(.0006)
F Stats	1.63	2.93	2.51	0.35	0.64	4.18	3.71	5.89	1.35	0.56	0.81	0.32
R^2	.038	.065	.042	.007	.013	.076	.078	.106	.025	.012	.014	.007
# Obs.	2107	2107	2107	2373	2373	2373	2373	2373	2373	2373	2373	2373
Panel B												
Prime Age	-.131***	-.127***	-.059***	.021	2.525***	-.139***	-.116***	.157***	-.055*	-.082	-.041	.082
Std. Err.	(.048)	(.037)	(.036)	(.028)	(.263)	(.019)	(.021)	(.050)	(.031)	(.063)	(.051)	(.069)
F Stats	1.60	3.06	2.53	0.33	2.25	5.35	4.25	6.10	1.50	0.59	0.80	0.33
R^2	.037	.067	.042	.006	.042	.097	.091	.111	.026	.013	.014	.008
# Obs.	2107	2107	2107	2373	2373	2373	2107	2107	2373	2373	2373	2373
Panel C												
Old Dep.	.0007**	.0005**	-.0002	-.0002	-.0073***	.0002**	1.9×10^{-5}	-.0008**	-.00003	-.0002	-.0003	-.0002
Std. Err.	(.0003)	(.0002)	(.0002)	(.0002)	(.0015)	(.0001)	(.0001)	(.0004)	(.0002)	(.0004)	(.0003)	(.0006)
F Stats	1.58	2.93	2.43	0.34	0.79	4.23	3.68	5.94	1.34	0.56	0.82	0.32
R^2	.037	.064	.042	.007	.017	.078	.078	.111	.025	.012	.014	.007
# Obs.	2107	2107	2371	2373	2373	2373	2107	2107	2373	2373	2373	2373
Panel D												
Over65	.0014**	.0009**	-.0005	-.0005	-.0149***	.0003	-.0002	-.0016**	-.0001	-.0003	-.0005	-.0005
Std. Err.	(.0006)	(.0004)	(.0004)	(.0003)	(.0028)	(.0002)	(.0003)	(.0006)	(.0003)	(.0007)	(.0006)	(.001)
F Stats	1.60	2.93	2.46	0.35	0.88	4.19	3.70	5.94	1.33	0.56	0.81	0.32
R^2	.037	.064	.042	.007	.018	.077	.078	.111	.025	.012	.014	.007
# Obs.	2107	2107	2371	2373	2373	2373	2107	2107	2373	2373	2373	2373
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.4: Results of 2SLS Models (Annual Growth)

	Economy			Local Market					Income			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	.0028**	.0019*	.0001	-.0005	-.0281***	.0013**	.001	-.0004	-.0008	.0008	.0009	-.0002
Std. Err.	(.0014)	(.001)	(.0011)	(.0008)	(.0078)	(.0006)	(.0006)	(.0014)	(.0009)	(.0017)	(.0014)	(.0016)
1st-stage F Stats	68.06	68.06	76.81	77.20	77.20	77.20	68.06	68.06	77.20	77.20	77.20	77.20
R^2	.027	.056	.038	.006	.000	.047	.053	.106	.022	.008	.009	.007
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
Panel B												
Prime Age	-.406***	-.393***	-.073	.053	6.134***	-.356***	-.342***	.405***	-.150*	-.186	-.169	.226
Std. Err.	(.143)	(.106)	(.106)	(.077)	(.793)	(.054)	(.065)	(.138)	(.087)	(.159)	(.131)	(.139)
1st-stage F Stats	52.83	52.83	52.83	60.04	60.04	60.04	52.83	52.83	60.04	60.04	60.04	60.04
R^2	.021	.043	.039	.005	.000	.044	.040	.099	.022	.010	.010	.004
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
Panel C												
Old Dep.	.002*	.001*	-.000	-.000	-.023***	.001***	.001*	-.001	.000	.001	.001	-.000
Std. Err.	(.0012)	(.0008)	(.0007)	(.0006)	(.0053)	(.0004)	(.0005)	(.0010)	(.0006)	(.0011)	(.0010)	(.0012)
1st-stage F Stats	61.47	61.47	57.64	59.27	59.27	61.47	61.47	59.27	59.27	59.27	59.27	
R^2	.021	.050	.038	.006	.000	.043	.054	.111	.023	.006	.005	.007
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
Panel D												
Over65	.0039**	.0027*	-.0004	-.0008	-.0437***	.002***	.0014*	-.0023	.0001	.0010	.0013	-.0008
Std. Err.	(.0019)	(.0014)	(.0013)	(.0011)	(.0095)	(.0007)	(.0008)	(.0017)	(.0011)	(.0019)	(.0017)	(.0019)
1st-stage F Stats	67.94	67.94	67.94	65.47	67.38	67.38	67.38	67.94	67.94	67.38	67.38	67.38
R^2	.025	.053	.039	.006	.000	.043	.054	.110	.023	.008	.007	.007
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.5: Results of OLS Models (10-Year Growth)

	Economy			Local Market					Income			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	.005	.004	-.009**	-.0004	.009	-.007***	-.007***	.002	.0005	-.0035	-.006***	-.003
Std. Err.	(.0038)	(.0038)	(.0046)	(.0016)	(.0118)	(.0020)	(.0021)	(.0047)	(.0025)	(.0026)	(.0020)	(.0023)
R^2	.346	.346	.384	.222	.322	.549	.529	.549	.499	.438	.465	.411
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel B												
Prime Age	.631	.740	.278	.041	-.676	.105	.096	.718	.159	.007	-.028	-.009
Std. Err.	(.6076)	(.6430)	(.8103)	(.1709)	(1.9184)	(.2966)	(.3110)	(.6812)	(.3289)	(.4726)	(.3721)	(.3115)
R^2	.343	.346	.374	.222	.319	.516	.491	.552	.500	.431	.443	.404
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel C												
Old Dep.	-.0005	-.0005	-.0052*	.0002	.0127	-.0022	-.0022	-.0034	-.0012	-.0034**	-.0033***	-.0027**
Std. Err.	(.0023)	(.0023)	(.0027)	(.0008)	(.0080)	(.0017)	(.0017)	(.0042)	(.0015)	(.0015)	(.0012)	(.0012)
R^2	.339	.342	.381	.222	.334	.524	.499	.553	.501	.444	.456	.414
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel D												
Over65	.0013	-.0002	-.0111*	-.0005	.0243	-.0063**	-.0065**	-.0058	-.0023	-.0063**	-.0064***	-.0042
Std. Err.	(.0049)	(.0048)	(.0057)	(.0019)	(.0147)	(.0032)	(.0033)	(.0073)	(.0030)	(.0030)	(.0024)	(.0026)
R^2	.340	.341	.382	.222	.334	.533	.509	.552	.501	.443	.455	.411
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.6: Results of 2SLS Models (10-Year Growth)

	Economy			Local Market					Income			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	.0174	.0070	.0112	-.0044	-.0125	.0079	.0086	.0307	-.0112	-.0178	-.0169	.0190
Std. Err.	(.0306)	(.0297)	(.0464)	(.0095)	(.0830)	(.0203)	(.0222)	(.0387)	(.0177)	(.0278)	(.0212)	(.0278)
1st-stage F Stats	24.69	24.08	24.08	24.69	24.69	24.08	24.08	24.08	24.08	24.08	24.08	24.08
R^2	.310	.344	.334	.174	.300	.389	.345	.413	.428	.330	.393	.051
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel B												
Prime Age	14.005	10.582	24.391	-4.256	-3.772	9.778	9.091	9.084	-2.788	-.0128	-2.063	4.733
Std. Err.	(24.99)	(23.07)	(50.80)	(8.456)	(26.29)	(19.39)	(18.22)	(22.61)	(9.952)	(9.161)	(8.420)	(12.43)
1st-stage F Stats	19.93	17.61	17.61	19.93	19.93	17.61	17.61	17.61	17.61	17.61	17.61	17.61
R^2	.000	.000	.000	.000	.301	.000	.000	.097	.323	.431	.365	.000
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel C												
Old Dep.	-.017	-.010	-.0189	.009	-.0113	-.004	-.003	.003	-.000	-.008	-.001	.016
Std. Err.	(.0246)	(.0232)	(.0348)	(.0110)	(.0590)	(.0135)	(.0143)	(.0319)	(.0134)	(.0162)	(.0158)	(.0199)
1st-stage F Stats	15245	17.00	17.00	15245	15245	17.00	17.00	17.00	17.00	17.00	17.00	17.00
R^2	.193	.294	.332	.000	.275	.520	.498	.537	.500	.417	.449	.000
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel D												
Over65	-.040	-.034	-.057	.014	-.073	-.006	-.006	.035	-.011	-.027	-.008	.044
Std. Err.	(.085)	(.081)	(.113)	(.028)	(.208)	(.039)	(.042)	(.106)	(-.041)	(.056)	(.048)	(.069)
1st-stage F Stats	30.21	42.38	42.38	30.21	30.21	42.38	42.38	42.38	42.38	42.38	42.38	42.38
R^2	.085	.198	.237	.000	.076	.533	.509	.398	.481	.313	.454	.000
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.7: Results of Time-Differenced OLS Models (Annual Growth)

	Economy			Local Market					Income			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	.198***	.092**	.041	-.133***	-.968**	-.057**	-.062**	-.130***	.108**	.042***	.054 * .223***	
Std. Err.	(.0579)	(.0457)	(.0488)	(.0387)	(.4569)	(.0279)	(.0289)	(.0464)	(.0424)	(.0907)	(.0665)	(.0720)
R^2	.0407	.0639	.0416	.0137	.0107	.0788	.0809	.1088	.0287	.0283	.0141	.0130
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
Panel B												
Prime Age	-.039	.097**	.15***	.114***	-2.639***	.137***	.014***	.016	.284***	.804***	.159**	.134*
Std. Err.	(.0522)	(.0392)	(.0409)	(.0359)	(.3821)	(.0249)	(.0253)	(.0402)	(.0370)	(.0745)	(.0622)	(.0685)
R^2	.0341	.0648	.0470	.0129	.0442	.0960	.0973	.1058	.0557	.0864	.0178	.0097
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
Panel C												
Old Dep.	.104***	.025	-.029	-.069***	-1.027***	.039***	.038**	-.060*	.003	.028	-.009	-.016
Std. Err.	(.0390)	(.0368)	(.0387)	(.0230)	(.2235)	(.0144)	(.0153)	(.0347)	(.0251)	(.0514)	(.0420)	(.0404)
R^2	.0389	.0620	.0417	.0114	.0191	.0795	.0810	.1075	.0250	.0119	.0138	.0071
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
Panel D												
Over65	.0911*	.0347	-.0280	-.0896***	-1.1544***	.0489***	.0496***	-.0865**	.0222	-.0052	-.0096	-.0131
Std. Err.	(.0447)	(.0411)	(.0445)	(.0270)	(.0266)	(.0174)	(.0186)	(.0397)	(.0305)	(.0608)	(.0484)	(.0484)
R^2	.0365	.0622	.0416	.0126	.0178	.0799	.0816	.1083	.0253	.0117	.0138	.0071
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.8: Results of Time-Differenced OLS Models (10-Year Growth)

	Economy			Local Market					Income			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	-.0713	-1.055*	-1.439**	-.2978***	-.0124	-.2483	-.2203	-.01157	-.5751**	-.0752	-.6022***	-.3339*
Std. Err.	(.5148)	(.5526)	(.6886)	(.0911)	(.6921)	(.1863)	(.1909)	(.2891)	(.2299)	(.2198)	(.2092)	(.2014)
R^2	.3672	.3956	.4279	.2802	.3177	.5257	.4989	.5487	.5362	.4316	.4892	.4269
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel B												
Prime Age	.5588	.9355*	1.473**	.2881**	-3.069***	.616***	.6537***	-.6000	.5261**	1.0783***	.5406**	.3515
Std. Err.	(.4570)	(.4875)	(.6365)	(.1119)	(.9644)	(.1904)	(.1947)	(.4990)	(.2445)	(.2709)	(.2406)	(.2151)
R^2	.0349	.3677	.4087	.2550	.3761	.5539	.5336	.5566	.5184	.5217	.4647	.4153
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel C												
Old Dep.	-.2558	-.3852*	-.6009**	-.1004***	.0041	-.1435*	-.1391*	.2127*	-.1979**	-.0987	-.2698***	-.1757**
Std. Err.	(.1982)	(.2151)	(.2729)	(.0365)	(.2567)	(.0748)	(.0771)	(.1248)	(.0983)	(.0886)	(.0839)	(.0719)
R^2	.3664	.3965	.4457	.2718	.3177	.5414	.5149	.5610	.5327	.4395	.5150	.4402
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel D												
Over65	-.3790	-.5223*	-.8316**	-.1238***	-.0597	-.2149**	-.2104**	.2999	-.2783**	-.1630	-.3428***	-.2429***
Std. Err.	(.2701)	(.2971)	(.3715)	(.0430)	(.3209)	(.0991)	(.1015)	(.1765)	(.1321)	(.1116)	(.1105)	(.0906)
R^2	.3783	.4075	.4636	.2717	.3179	.5533	.5267	.5646	.5423	.4461	.5190	.4493
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.9: Results of Time-Differenced 2SLS Models (Annual Growth)

	Economy			Local Market					Income			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	.870***	.544**	.350	-.276	-4.763**	-.0156	-.0292	-.437	.593***	1.125***	.743**	.842***
Std. Err.	(.306)	(.224)	(.243)	(.190)	(2.120)	(.141)	(.138)	(.244)	(.217)	(.380)	(.328)	(.315)
1st-stage F Stats	13.42	13.42	11.60	11.67	11.67	11.67	13.42	13.42	11.67	11.67	11.67	11.67
R^2	.1067	.1426	.1061	.0834	.5010	.5205	.5265	.0930	.4624	.1278	.1137	.0001
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
Panel B												
Prime Age	-.0714	.207*	.347**	.259**	-7.959***	.412***	.416**	-.0883	.896***	1.031***	.443**	.326*
Std. Err.	(.166)	(.122)	(.137)	(.123)	(1.536)	(.099)	(.100)	(.154)	(.156)	(.215)	(.195)	(.192)
1st-stage F Stats	13.64	13.64	15.91	15.91	15.91	15.91	13.64	13.64	15.91	15.91	15.91	15.91
R^2	.0923	.0913	.0958	.1161	.4960	.5126	.5177	.0919	.4629	.1354	.1029	.0473
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
Panel C												
Old Dep.	.513*	.656***	.391*	.126	-8.457***	.480***	.453***	-.123	.187	.526	.421	-.164
Std. Err.	(.263)	(.218)	(.216)	(.143)	(1.898)	(.126)	(.130)	(.204)	(.149)	(.339)	(.265)	(.296)
1st-stage F Stats	50.35	50.35	53.34	54.33	54.33	54.33	50.35	50.35	54.33	54.33	54.33	54.33
R^2	.1107	.1107	.0001	.1240	.4623	.5236	.4968	.0001	.4325	.0001	.0001	.0001
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
Panel D												
Over65	.923**	.993***	.660**	.0516	-11.57***	.627***	.586***	-.223	.293	.510	.434	-.106
Std. Err.	(.389)	(.318)	(.313)	(.189)	(2.633)	(.176)	(.177)	(.267)	(.208)	(.452)	(.343)	(.387)
1st-stage F Stats	51.96	51.96	53.78	54.97	54.97	54.97	51.96	51.96	54.97	54.97	54.97	54.97
R^2	.0001	.0001	.0001	.0001	.2772	.4539	.5197	.0001	.4399	.0001	.0547	.0001
# Obs.	2081	2081	2340	2342	2342	2342	2081	2081	2342	2342	2342	2342
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.10: Results of Time-Differenced 2SLS Models (10-Year Growth)

	Economy			**Local Market**					**Income**			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	-2.154	-3.675	-7.323	-.460	-4.804	-3.374	-3.754	2.047	-.417	.349	-1.110	1.768
Std. Err.	(3.173)	(5.029)	(9.698)	(.822)	(10.230)	(4.686)	(5.159)	(5.021)	(1.922)	(2.246)	(2.119)	(3.278)
1st-stage F Stats	11.28	11.11	12.66	12.93	12.93	12.66	11.11	11.11	12.66	12.66	12.66	12.66
R^2	.0698	.0225	.0001	.0060	.0001	.0001	.0001	.0001	.0497	.0001	.1465	.0001
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel B												
Prime Age	2.393	-1.329	-3.450	-2.211	1.796	.519	.310	7.459	-.568	1.975	1.810	1.270
Std. Err.	(4.547)	(6.525)	(10.50)	(2.712)	(10.03)	(3.175)	(3.343)	(12.24)	(3.634)	(3.333)	(3.587)	(3.170)
1st-stage F Stats	19.16	20.74	24.34	23.02	23.02	24.34	20.74	20.74	24.34	24.34	24.34	24.34
R^2	.0508	.0001	.2439	.0001	.0567	.1859	.1240	.0001	.0349	.1566	.0744	.0146
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel C												
Old Dep.	2.619	.722	-1.474	-1.255	-.980	-.653	-.908	4.077	-1.252	1.219	-.320	.0648
Std. Err.	(6.998)	(2.795)	(3.275)	(2.917)	(8.553)	(1.779)	(2.173)	(8.126)	(2.867)	(3.050)	(1.353)	(1.406)
1st-stage F Stats	2.85	2.68	2.74	2.83	2.83	2.74	2.68	2.68	2.74	2.74	2.74	2.74
R^2	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.1505	.0001
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
Panel D												
Over65	-2.683	-1.145	.901	1.116	1.052	1.018	1.205	-2.239	1.367	-1.462	.189	.153
Std. Err.	(4.849)	(2.483)	(3.941)	(2.560)	(7.189)	(2.710)	(3.101)	(6.301)	(3.224)	(3.075)	(1.557)	(1.582)
1st-stage F Stats	3.97	4.21	4.71	4.66	4.66	4.71	4.21	4.21	4.71	4.71	4.71	4.71
R^2	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001	.0001
# Obs.	256	261	261	256	256	261	261	261	261	261	261	261
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.11: Results of OLS Models (Before Recession)

	Economy			Local Market					Income			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	.0000	-.0006	-.0028***	-.0006	.0110*	-.0008**	-.0007**	.0011	-.0006	-.0001	-.0012	-.0014
Std. Err.	(.0016)	(.0011)	(.0010)	(.0009)	(.0057)	(.0003)	(.0003)	(.0018)	(.0006)	(.0015)	(.0015)	(.0013)
R^2	.253	.336	.416	.184	.363	.491	.471	.542	.391	.276	.257	.162
# Obs.	261	261	261	261	261	261	261	261	261	261	261	261
Panel B												
Prime Age	.2337	.1298	.0040	-.0406	.3784	.0561	.0461	.5465**	-.0304	.3222	.4685**	.0510
Std. Err.	(.1655)	(.1368)	(.1432)	(.0897)	(.9084)	(.0641)	(.0641)	(.2759)	(.0645)	(.2372)	(.2068)	(.1941)
R^2	.259	.338	.384	.182	.350	.478	.459	.556	.387	.284	.276	.158
# Obs.	261	261	261	261	261	261	261	261	261	261	261	261
Panel C												
Old Dep.	-.0011	-.0010	-.0016***	.0001	.0068**	-.0004**	-.0003**	-.0022	-.0005	-.0015	-.0024***	-.0009
Std. Err.	(.2597)	(.3456)	(.4056)	(.1820)	(.3604)	(.4839)	(.4625)	(.5535)	(.3931)	(.2850)	(.2858)	(.1616)
R^2	.260	.346	.406	.182	.360	.484	.463	.554	.393	.285	.286	.162
# Obs.	261	261	261	261	261	261	261	261	261	261	261	261
Panel D												
Over65	-.0016	-.0017	-.0032***	.0001	.0124**	-.0009**	-.0008**	-.0033	-.0010	-.0023	-.0042**	-.0016
Std. Err.	(.0020)	(.0013)	(.0012)	(.0011)	(.0068)	(.0004)	(.0004)	(.0029)	(.0008)	(.0019)	(.0020)	(.0015)
R^2	.257	.343	.407	.182	.359	.486	.465	.548	.394	.282	.281	.161
# Obs.	261	261	261	261	261	261	261	261	261	261	261	261
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.12: Results of OLS Models (During Recession)

	Economy			Local Market					Income			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	.0006	.0000	-.0013*	-.0004	.0030	-.0008***	-.0011***	.0001	-.0011*	-.0004	-.0009	-.0011
Std. Err.	(.0008)	(.0007)	(.0008)	(.0005)	(.0050)	(.0003)	(.0003)	(.0006)	(.0006)	(.0012)	(.0009)	(.0008)
R^2	.054	.088	.084	.030	.030	.217	.251	.058	.040	.040	.028	
# Obs.	791	791	790	791	791	791	791	791	791	791	791	791
Panel B												
Prime Age	-.331***	-.224**	-.240**	.114	-.237	-.077*	-.079*	.010	-.090	-.004	.023	-.093
Std. Err.	(.1118)	(.0920)	(.1009)	(.0738)	(.8394)	(.0416)	(.0433)	(.0787)	(.0952)	(.1863)	(.1219)	(.1176)
R^2	.063	.095	.086	.033	.030	.210	.203	.251	.056	.0400	.039	.027
# Obs.	791	791	790	791	791	791	791	791	791	791	791	791
Panel C												
Old Dep.	.0009	.0003	-.0005	-.0006	.0031	-.0004**	-.0006**	-.0003	-.0007*	-.0004	-.0007	-.0002
Std. Err.	(.0007)	(.0005)	(.0005)	(.0004)	(.0036)	(.0002)	(.0002)	(.0004)	(.0004)	(.0009)	(.0008)	(.0007)
R^2	.057	.089	.081	.033	.031	.211	.208	.252	.057	.040	.041	.026
# Obs.	791	791	790	791	791	791	791	791	791	791	791	791
Panel D												
Over65	.0019*	.0006	-.0010	-.0011	.0059	-.0009**	-.0012***	-.0005	-.0012	-.0008	-.0011	-.0004
Std. Err.	(.0012)	(.0009)	(.0010)	(.0007)	(.0067)	(.0004)	(.0004)	(.0008)	(.0008)	(.0016)	(.0014)	(.0012)
R^2	.057	.089	.081	.033	.031	.213	.210	.252	.057	.040	.040	.026
# Obs.	791	791	790	791	791	791	791	791	791	791	791	791
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Table A.13: Results of OLS Models (After Recession)

	Economy			Local Market					Income			
	per worker	per capita	GDP	LFPR	Unemp	Jobtot	Jobnf	Jobf	average	med16	med25	mean
Panel A												
Median Age	.0007*	.0006**	-.0002	-.0003	-.0040**	-.0003**	-.0004**	-.0004	-.0001	-.0005	-.0002	.0004
Std. Err.	(.0005)	(.0003)	(.0003)	(.0003)	(.0016)	(.0001)	(.0001)	(.0005)	(.0002)	(.0007)	(.0006)	(.0008)
R^2	.0867	.1503	.0960	.0154	.0349	.2303	.2350	.1396	.0504	.0171	.0179	.0125
# Obs.	1055	1055	1320	1321	1321	1321	1055	1055	1321	1321	1321	1321
Panel B												
Prime Age	.135**	.138***	.142***	-.003	.344	.067***	.088***	.007	.103***	-.108	-.031	.044
Std. Err.	(.0609)	(.0413)	(.0408)	(.0402)	(.2396)	(.0175)	(.0202)	(.0588)	(.0376)	(.0861)	(.0736)	(.1139)
R^2	.0880	.1547	.1026	.0144	.0317	.2354	.2441	.1389	.0559	.0178	.0180	.0124
# Obs.	1055	1055	1320	1321	1321	1321	1055	1055	1321	1321	1321	1321
Panel C												
Old Dep.	.0003	.0002	-.0002	-.0002	-.0028**	-.0001	-.0002*	-.0003	-.0000	.0001	.0001	.0003
Std. Err.	(.0004)	(.0002)	(.0002)	(.0002)	(.0011)	(.0001)	(.0001)	(.0004)	(.0002)	(.0005)	(.0004)	(.0010)
R^2	.0843	.1466	.0960	.0152	.0346	.2272	.2322	.1397	.0502	.0166	.0179	.0127
# Obs.	1055	1055	1320	1321	1321	1321	1055	1055	1321	1321	1321	1321
Panel D												
Over65	.0006	.0004	-.0006	-.0004	-.0059***	-.0004**	-.0006***	-.0006	-.0001	.0003	.0002	.0005
Std. Err.	(.0007)	(.0004)	(.0004)	(.0004)	(.0022)	(.0002)	(.0002)	(.0007)	(.0003)	(.0009)	(.0008)	(.0016)
R^2	.0844	.1468	.0970	.0152	.0355	.2305	.2375	.1397	.0503	.0167	.0179	.0125
# Obs.	1055	1055	1320	1321	1321	1321	1055	1055	1321	1321	1321	1321
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
edu, race, sex	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: 1. *, **, *** indicates the coefficients are significant at 10%, 5% and 1% level respectively.
2. Standard errors, which are robust to heteroskedasticity, are reported in parenthesis.
3. The numbers of observations are different due to missing data.

Figure A.2: Coefficients of Age Structures in Quantile Regressions using GDP as Dependent Variables (Annual Growth)

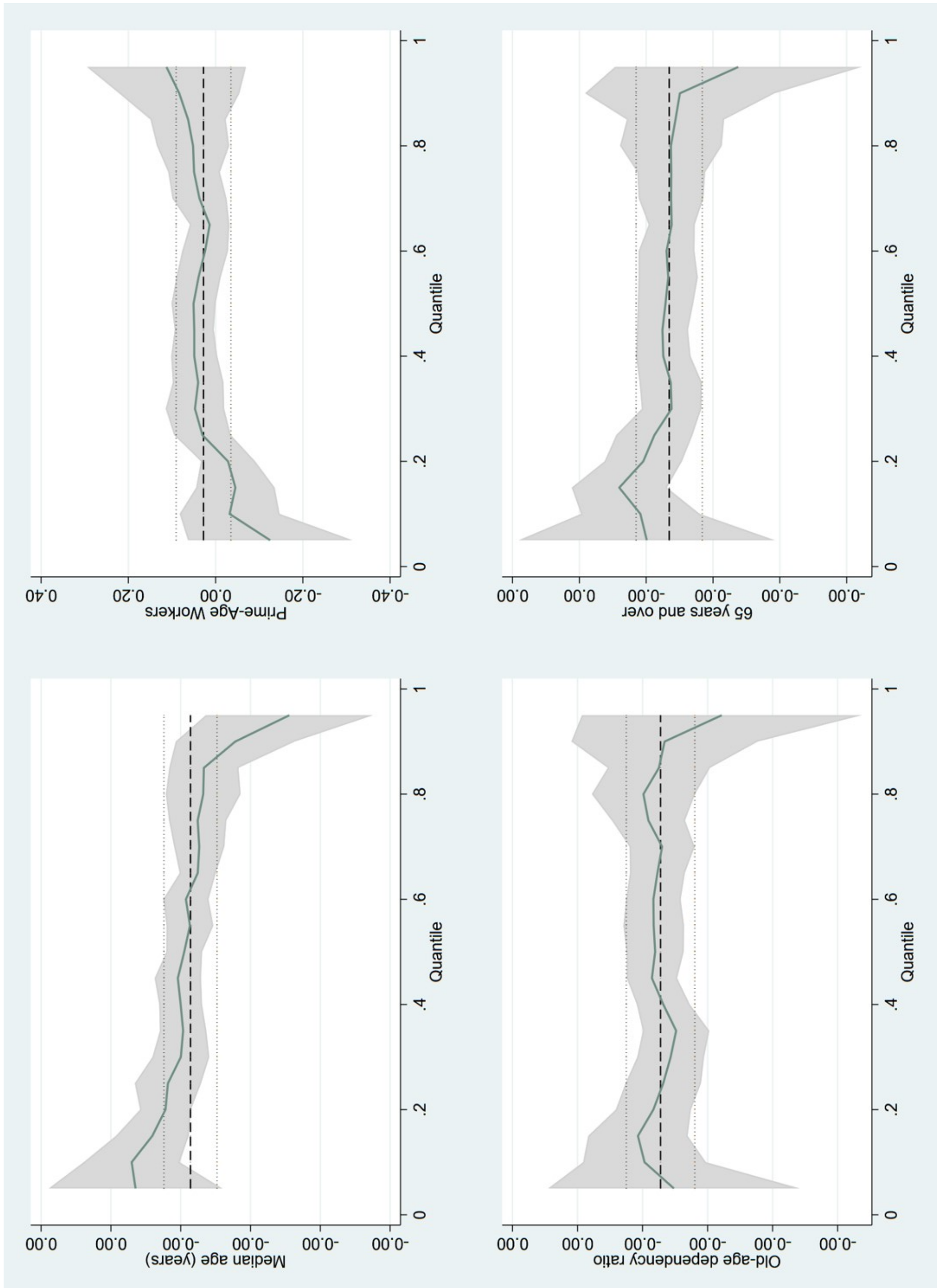


Figure A.3: Coefficients of Age Structures in Quantile Regressions using GDP as Dependent Variables (10-Year Growth)

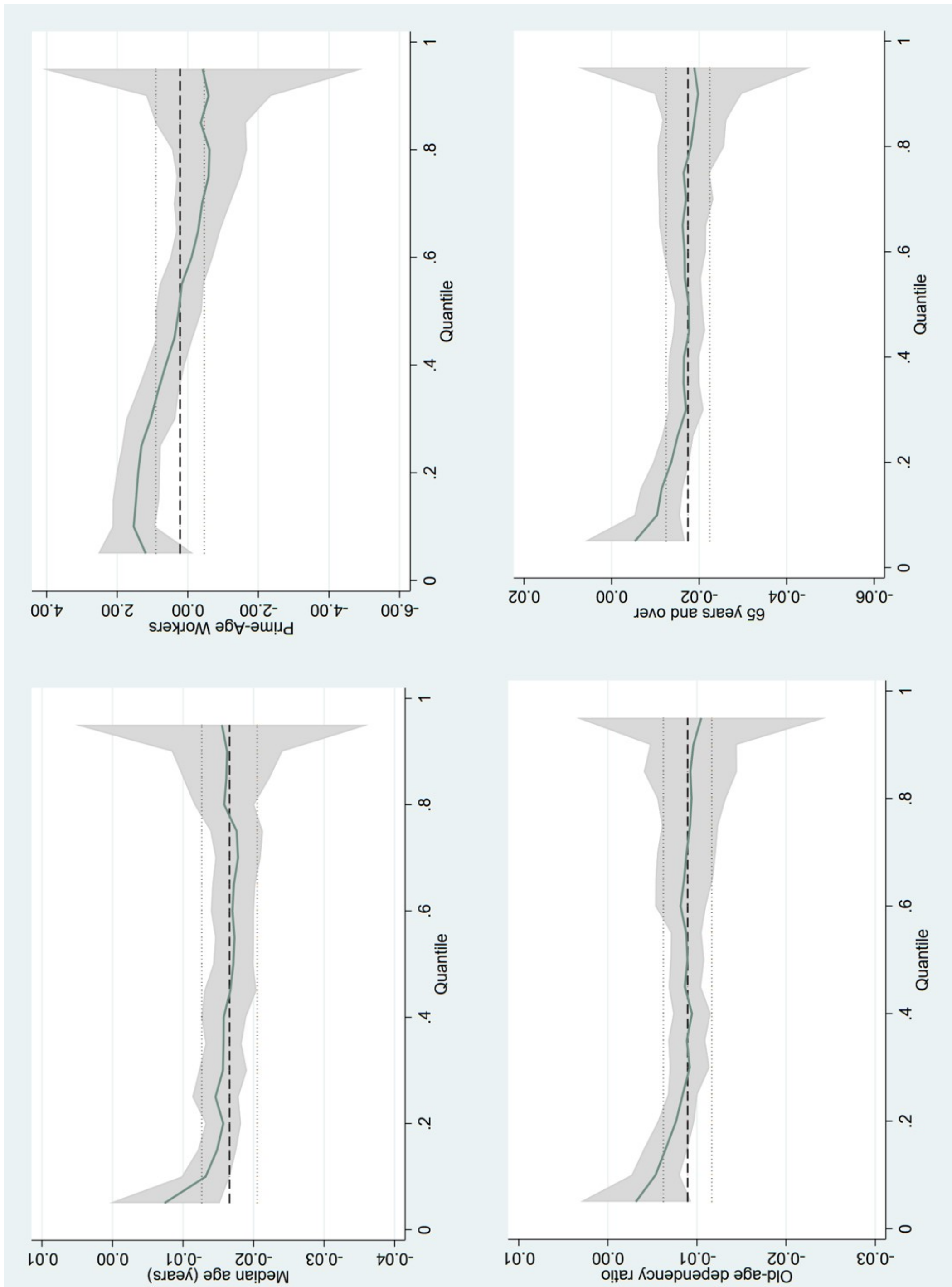


Figure A.4: Coefficients of Age Structures in Quantile Regressions using Unemployment Rates as Dependent Variables (Annual Growth)

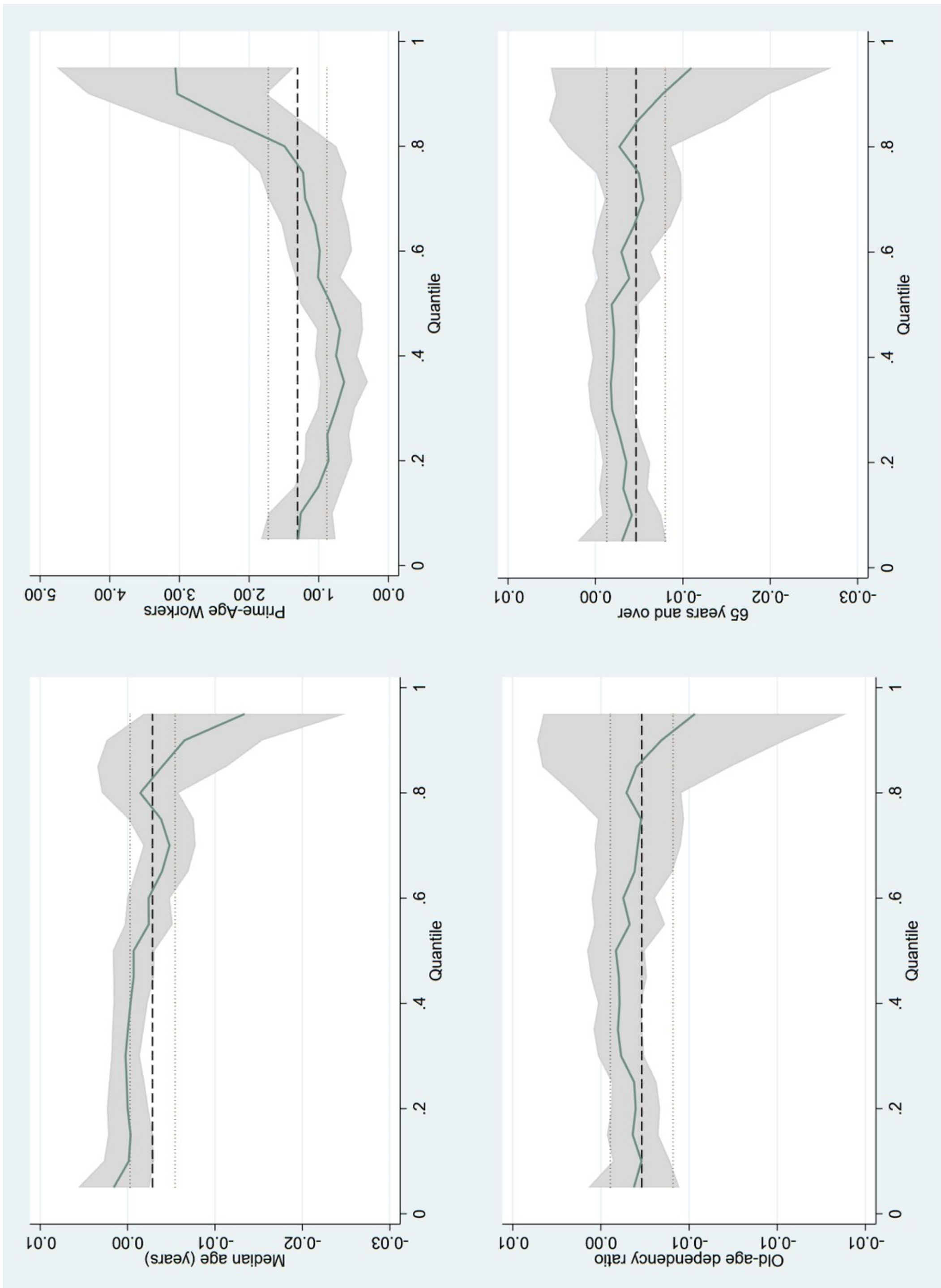


Figure A.5: Coefficients of Age Structures in Quantile Regressions using Unemployment Rates as Dependent Variables (10-Year Growth)