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DEMOGRAPHIC STRUCTURE AND HOUSE PRICES IN THE UNITED STATES: RECONCILIATION USING METROPOLITAN AREA DATA*

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We apply a semiparametric approach to 19 metropolitan areas in the US to relate normalized house prices to the age distribution within each area. We find that, although the elderly population has a negative impact on house prices in most areas, the shape of the estimated age response function differs between areas. We further find via probit and logit regressions that the age-response function is more likely to become inverted U-shaped as the population of an area becomes more aged, which is also suggestive of the negative impact of aging. These results indicate that the impact of the elderly population becomes more negative as the population ages.

Keywords: Demographic Structure, Population Aging, House Prices, Semiparametric Approach, Probit Regression
JEL Classification: G12, J11, R30

1. INTRODUCTION

Many advanced economies are experiencing rapid aging as a result of a drastic decline in fertility and death rates. For this reason, policymakers, investors, households, and economists are eager to understand the impact of aging on house prices. Two opposing views have been reported in the literature. Mankiw and Weil (1989), Takáts (2012), and Jäger and Schmidt (2017) argue that an increase in the share of the elderly population has a negative impact on house prices due to life cycle savings. That is, the prime working age generation increases the size of houses and raises house prices, whereas the elderly generation reduces house sizes and lowers house prices. Hiller and Lerbs (2016) also show that the growth rate of urban housing prices tends to be low in German cities where the population ages rapidly. In contrast, Green and Hendershott

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(1996) argue that the aging of the population does not lower housing prices after controlling for education and income. Lisack et al. (2017) demonstrate that the real interest rate is lower in an aging economy, which raises house prices. Hort (1998) also finds a positive impact of aging.

In the present study, we provide empirical evidence for the relationship between the demographic structure and house prices. We relate overall age distributions to house prices in 19 metropolitan areas in the US without imposing an a priori functional form on this relation. Consistent with the results of previous studies, we find both negative and positive impacts of aging, although most areas show a negative impact. We reconcile these conflicting results using the difference in the shapes of the estimated age response functions. We demonstrate that, when the share of the elderly population reaches a certain threshold, the relationship between the population distribution and normalized house prices changes. In particular, when the proportion of the elderly population is low, i.e., below the threshold, we observe a positive impact of aging on house prices. However, when the size of the elderly population relative to the working population exceeds the threshold, the age response functions tend to become inverted U-shaped, and the impact of the elderly population is more likely to be negative. We examine this hypothesis by conducting probit and logit regressions and show that, as the population of an area becomes older, the age response function is more likely to become inverted U-shaped, which illustrates the negative impact of the elderly population on house prices.

This paper is organized as follows. Section 2 presents the econometric methodology employed in this paper, while Section 3 briefly discusses the data and Section 4 provides the main empirical analysis. Concluding remarks are presented in Section 5.

2. ECONOMETRIC MODEL

To examine the relationship between the demographic structure and house prices, we consider the following econometric model:

$$y_t = \mu + \int_T f_t(m)\, g(m) dm + \beta' X_t + u_t, \tag{1}$$

where y_t is the log price-rent ratio, f_t denotes the density function of the age distribution at time t, T is the common compact support for f_t, and X_t includes control variables other than the population age distribution. The log price-rent ratio (y_t) is the normalized house price and can be interpreted as the price-dividend ratio or price-earnings ratio in the stock market. That is, it is widely used as an indicator to determine whether house prices are correctly valued. Because of this economic meaning, the price-rent ratio has been examined in previous studies such as Himmelberg et al. (2005), Campbell et al. (2009) and Kishor and Morley (2015). As Campbell et al. (2009) and Kishor and Morley (2015) demonstrate that (expected) changes in house prices explain a significant fraction of the log price-rent ratio variability at the metropolitan level in the US, the dynamics of the log price-rent ratio is more likely to be related with changes in house prices than rents. In addition, y_t should follow a stationary process in order for a semiparametric approach to be employed in Equation (1) (see Andrews, 1991). For these reasons, the log price-rent ratio is used for y_t rather than the house prices in this study.

Because the regressor f_t is the density function of age distribution, $\int_{T_j} f_t(m)\, dm$ (where T_j is a subinterval of T) is the fraction of individuals in age group T_j for the total population. Because we are relating the variation in the price-rent ratio to the variation in the entire age distribution (f_t), we can avoid any arbitrariness arising from the choice of a specific age range or a particular demographic measure.[1] $g(m)$ in regression Equation (1) can be interpreted as the age response function that reflects the impact of the population age distribution on the price-rent ratio. As control variables, we include the growth rate of the regional population and the growth rate of the regional per capita income deflated by the corresponding regional consumer price index (CPI). Because migration between regions could be driven by current and expected income, which eventually affects the price–rent ratio, we include the growth rate of per capita income in addition to the demographic structure.

Once an estimate for $g(m)$ is obtained, the age group that has a significant impact on the movement of the price-rent ratio can be determined, and the estimate of $g(m)$ can be compared with the implications of the theoretical models. Assuming a special form for $g(m)$, previous studies have considered the variants of the econometric model in Equation (1) to examine the relationship between the demographic structure and macroeconomic or financial variables. For example, the econometric model in Mankiw and Weil (1989) can be interpreted as a special case in which $g(m)$ is linear. Assuming a quadratic function for $g(m)$, Fair and Dominguez (1991) examine consumption and saving decisions. Higgins (1998) and Jäger and Schmidt (2017) assume a cubic function for $g(m)$ to estimate the impact of the age distribution on international capital flow and house prices, respectively.

Unlike the above-mentioned studies, we do not impose an *a priori* special function for $g(m)$, which is consistent with Park (2010) in the sense that a flexible approach is employed. Instead, we assume that $g(m)$ must be sufficiently smooth to be approximated by a series of polynomials, trigonometric functions, or a mixture of both. That is, we assume that $\|g_\kappa - g\| \to 0$ as $\kappa \to \infty$, where $g_\kappa(m)$ is an approximation of $g(m)$ given by a combination of a finite series of functions $\varphi_1, \cdots, \varphi_\kappa$. When $g_\kappa(m) = \sum_{j=1}^{\kappa} \alpha_j\, \varphi_j(m)$, Equation (1) can be expressed in a straightforward manner as

$$y_t = \mu + \sum_{j=1}^{\kappa} \alpha_j \int_T\, f_t(m)\, \varphi_j(m) dm + \beta' X_t + u_{\kappa,t} = \mu + z_t a_\kappa + u_{\kappa,t}, \tag{2}$$

[1] Jäger and Schmidt (2017) instrument f_t based on past age distributions and show that the results are robust whether f_t is instrumented or not. Hence, we use f_t in the regression rather than instrumenting it.

where $u_{\kappa,t} = u_t + \int_T f_t(m)\,(g - g_\kappa)(m)dm$, $a_\kappa = [\alpha_1, \dots, \alpha_\kappa, \beta']$ and $z_t = [\int_T f_t(m)\,\varphi_1(m)dm, \dots, \int_T f_t(m)\,\varphi_\kappa(m)dm,\ X_t']$. Allowing Y and Z to be vectors for y_t and z_t, respectively, the LS estimator for a_κ can be written as $\hat{a}_\kappa = (Z'Z)^{-1}Z'Y$. Then, the corresponding series estimator for the age response function can be expressed as

$$\hat{g}(m_h) = \sum_{j=1}^{\kappa} \hat{\alpha}_j\, \varphi_j(m_h), \tag{3}$$

where m_h is an interval in T.

In the empirical analysis, we test various series functions such as polynomials and mixtures of both polynomials and trigonometric functions, referred to as the Fourier flexible form (FFF) in Gallant (1981). The polynomial expansion of $g(m)$ can be written as $g_\kappa(m) = \alpha_1 m + \alpha_2 m^2 + \cdots + \alpha_\kappa m^\kappa$, and the FFF expansion of $g(m)$ can be expressed as $g_\kappa(m) = \alpha_1 m + \alpha_2 m^2 + \sum_{j=1}^{J}[\alpha_{3,j}\,cos(2\pi jm) + \alpha_{4,j} sin(2\pi jm)]$, where $\kappa = 2 + 2J$. The selection of κ (or, equivalently, the selection of J in the FFF expansion) is made based on h-block cross-validation (CV) and modified h-block CV criteria (MCV), as suggested by Burman et al. (1994) and Racine (1997), respectively. The CV can be expressed as

$$CV = N^{-1} \sum_{t=h}^{N-h} (y_t - z_t' \hat{a}_\kappa(t,h))^2, \tag{4}$$

where $\hat{a}_\kappa(t,h)$ is the estimators of the coefficients in Equation (2) obtained by removing the *t*-th observation and the h observations preceding and following the *t*-th observation for the dependent and independent variables in the regression. The modified h-block CV criterion, motivated by cases where $\frac{\kappa}{N}$ is not negligible, can be written as

$$MCV = N^{-1} \sum_{t=h}^{N-h} (y_t - z_t' \hat{a}_\kappa(t,h))^2 + N^{-2} \sum_{t=h}^{N-h} \sum_{i=1}^{N} (y_i - z_i' \hat{a}_\kappa(t,h))^2 + N^{-1} \sum_{i=1}^{N} (y_i - z_i' \hat{a}_\kappa)^2. \tag{5}$$

The κ that minimizes CV or MCV is selected in the analysis.

3. DATA

We estimate the age response functions for 19 metropolitan areas in the US. These areas and the sample periods are listed in Table 1. The 19 metropolitan areas are selected because data for the rent of primary residences published by the Bureau of Labor Statistics (BLS), which is used as the tenant rent index in this study, is available for these areas.[2] Assuming that the rent paid by tenants is identical to the rent accruing to owner-occupiers, tenant rent indices for the 19 areas from the BLS are used. With the exception of Baltimore, Miami, Tampa, and Washington DC, the sample period is 1975-2019. House price indices are taken from the Federal Housing Finance Agency. We adjust the rent scales using the average price–rent ratio for the corresponding areas in Campbell et al. (2009).3 Population structure data for the sampled areas are extracted from the US Census Bureau, and we use population estimates for 14 five-year age groups (ages 20-24, 25-29, …, 80-84, and 85 or above) to construct the annual age distribution. Regional population growth rates are also taken from the US Census Bureau. Finally, regional data for per capita income and the CPI are extracted from the Bureau of Economic Analysis and the BLS, respectively. All variables in this study are annual.

Table 1. Metropolitan Areas and Sample Periods

Metropolitan Area	Sample Period
Atlanta-Sandy Springs-Roswell, GA	1975–2019
Baltimore-Columbia-Towson, MD	1998–2019
Boston-Cambridge-Newton, MA-NH	1975–2019
Chicago-Naperville-Elgin, IL-IN-WI	1975–2019
Dallas-Fort Worth-Arlington, TX	1975–2019
Denver-Aurora-Lakewood, CO	1975–2019
Detroit-Warren-Dearborn, MI	1975–2019
Houston-The Woodlands-Sugar Land, TX	1975–2019
Los Angeles-Long Beach-Anaheim, CA	1975–2019
Miami-Fort Lauderdale-West Palm Beach, FL	1977–2019
Minneapolis-St.Paul-Bloomington, MN-WI	1975–2019
New York-Newark-Jersey City, NY-NJ-PA	1975–2019
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1975–2019
San Diego-Carlsbad, CA	1975–2019
San Francisco-Oakland-Hayward, CA	1975–2019
Seattle-Tacoma-Bellevue, WA	1975–2019
St. Louis, MO-IL	1975–2019
Tampa-St. Petersburg-Clearwater, FL	1987–2019
Washington DC-Arlington-Alexandria, DC-VA-MD-WV	1998–2019

[2] The BLS publishes the index for the rent of primary residences for 23 metropolitan areas. Of these, the Phoenix-Mesa-Scottsdale area (2002–2019) in Arizona and the Riverside-San Bernardino-Ontario area (2017-2019) in California are not used because the period for the index is too short. Urban Alaska and urban Hawaii are also excluded because these two areas are not on the US mainland.

[3] The rent scales for Baltimore, Tampa, and Washington DC, which are not analyzed in Campbell et al. (2009), are adjusted using the national average price–rent ratio for the US.

4. EMPIRICAL RESULTS

Because we cannot expand $g(m)$ with an infinite number of functions, it is important to determine the number of series functions that should be included to achieve a good approximation. We use various series functions to compute CV and MCV. In computing CV and MCV, the block size, h, is set as the integer nearest to $N/6$ following the suggestion by Burman et al. (1994). The results are shown in Table 2, with the lowest CV and MCV for a given metropolitan area denoted by the use of bold text. The selected series functions differ between the 19 metropolitan areas, although the quadratic form is chosen most frequently.[4]

Because different series functions are selected for different areas, we run the semiparametric regression in Equation (1) separately for individual areas rather than a pooled regression. Table 3 presents the estimated coefficients for the growth rates for the regional per capita income and regional population growth. The coefficients for the regional per capita income growth rate are negative but insignificant in most cases. The coefficients for regional population growth are positive in 12 of the 19 cases, with four of these significant.

Figures 1 and 2 present the estimated age response functions for all areas in our study. Estimated age responses show different impacts of each age group on the price-rent ratio. Newey-West standard errors are used to construct the 95% confidence interval for the age response functions. Because different series functions are employed for different areas, the shapes of the estimated age response functions also differ between areas. However, the shapes of the age response functions can be categorized into two types, as presented in Figures 1 and 2.

The estimated age response functions in Figure 1 are consistent with the life cycle hypothesis, indicating that the working age population has a positive impact and the elderly population has a negative impact on house prices. Overall, 13 metropolitan areas out of the 19 under study have this type of age response function, i.e., inverted U-shaped (Type 1), and the negative impact of aging in this group is consistent with the results in Mankiw and Weil (1989), Takáts (2012), and Jäger and Schmidt (2017). In contrast, the estimated age response functions shown in Figure 2 are compatible with Hort (1998) and Lisack et al. (2017), who report a positive impact of the elderly population on house prices. Six metropolitan areas are categorized as exhibiting this pattern (Type 2). Figures 3 and 4 show that the fitted values from semiparametric regression track the actual price-rent ratios quite closely, regardless of the shape of the estimated age response function.

[4] For a given metropolitan area, CV and MCV always indicate the same series function except for St. Louis. For St. Louis, there are slight differences in the CV and MCV between the quadratic and cubic polynomials. Because Racine (1997) demonstrates that MCV performs better with a non-negligible $\frac{\kappa}{N}$, we use the cubic polynomial based on MCV for the estimation for St. Louis.

Table 2. h-block and Modified h-block Cross-Validation Criteria

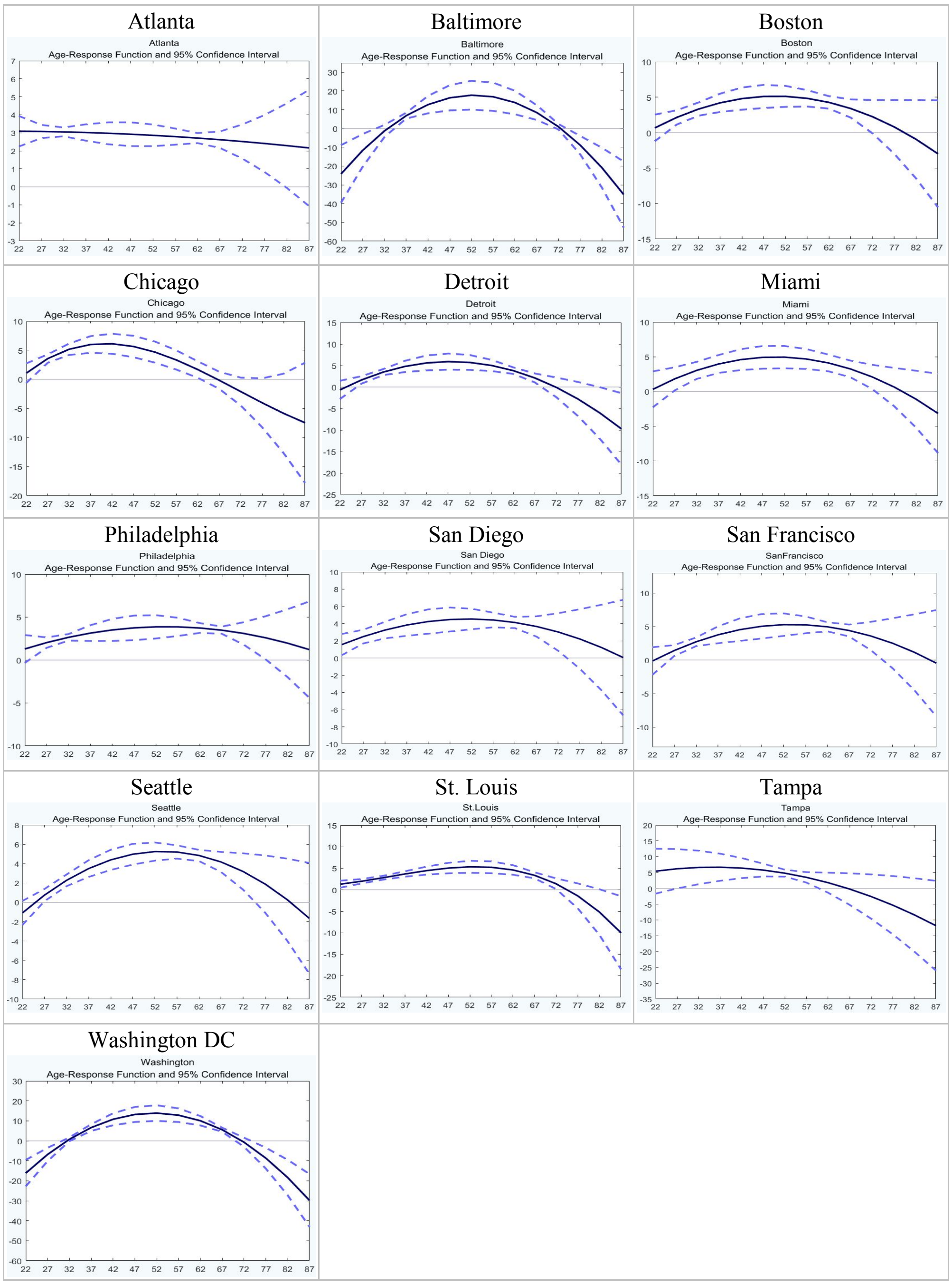
		Quadratic Polynomial	Cubic Polynomial	FFF $J = 1$	FFF $J = 2$	FFF $J = 3$	FFF $J = 4$
Atlanta	CV	**0.017**	0.020	0.027	0.032	0.047	0.071
	MCV	**0.028**	0.030	0.039	0.043	0.059	0.086
Baltimore	CV	**0.038**	0.079	0.123	0.141	0.146	14.021
	MCV	**0.055**	0.128	0.179	0.226	0.230	16.491
Boston	CV	**0.081**	0.134	0.229	0.180	0.305	0.394
	MCV	**0.129**	0.185	0.308	0.228	0.375	0.476
Chicago	CV	0.021	**0.017**	0.065	0.258	0.504	0.348
	MCV	0.036	**0.032**	0.102	0.332	0.623	0.485
Dallas	CV	**0.009**	0.022	0.056	0.028	0.023	0.046
	MCV	**0.015**	0.030	0.072	0.036	0.029	0.060
Denver	CV	**0.013**	0.071	0.143	0.083	0.133	0.213
	MCV	**0.029**	0.103	0.194	0.105	0.165	0.264
Detroit	CV	**0.061**	0.088	0.088	0.129	0.208	0.340
	MCV	**0.094**	0.128	0.132	0.197	0.293	0.460
Houston	CV	**0.017**	0.034	0.060	0.022	0.024	0.067
	MCV	**0.025**	0.049	0.083	0.029	0.032	0.087
Los Angeles	CV	0.066	0.097	**0.060**	0.147	0.501	0.698
	MCV	0.110	0.145	**0.102**	0.235	0.657	0.897
Miami	CV	**0.185**	0.343	0.778	0.762	0.478	0.877
	MCV	**0.594**	0.845	1.305	1.044	0.769	1.155
Minneapolis	CV	0.052	0.048	**0.031**	0.156	0.121	0.177
	MCV	0.081	0.074	**0.045**	0.199	0.150	0.268
New York	CV	0.204	0.206	**0.130**	0.165	0.206	0.166
	MCV	0.294	0.278	**0.168**	0.209	0.248	0.199
Philadelphia	CV	**0.028**	0.041	0.061	0.088	0.256	0.140
	MCV	**0.042**	0.057	0.085	0.112	0.313	0.174
San Diego	CV	**0.037**	0.040	0.039	0.194	0.422	0.371
	MCV	**0.068**	0.072	0.070	0.289	0.551	0.485
San Francisco	CV	**0.041**	0.057	0.140	0.586	1.681	0.983
	MCV	**0.080**	0.098	0.196	0.712	2.053	1.205
Seattle	CV	**0.019**	0.041	0.064	0.139	0.211	0.291
	MCV	**0.041**	0.068	0.098	0.195	0.263	0.358
St. Louis	CV	**0.0203**	0.0206	0.057	0.051	0.158	0.167
	MCV	0.0337	**0.0334**	0.098	0.081	0.238	0.253
Tampa	CV	**0.065**	0.282	0.262	0.223	0.322	0.156
	MCV	**0.099**	0.403	0.358	0.317	0.456	0.192
Washington DC	CV	**0.040**	1.155	0.417	1.011	0.788	0.616
	MCV	**0.067**	2.006	0.669	1.755	1.272	0.918

Note: The polynomial expansion of $g(m)$ can be written as $g_\kappa(m) = \alpha_1 m + \alpha_2 m^2 + \cdots + \alpha_\kappa m^\kappa$, and the Fourier flexible form (FFF) expansion of $g(m)$ can be expressed as $g_\kappa(m) = \alpha_1 m + \alpha_2 m^2 + \sum_{j=1}^{J}[\alpha_{3,j}\, cos(2\pi jm) + \alpha_{4,j} sin(2\pi jm)]$.

Table 3. Coefficients for Regional Per Capita Income Growth and Regional Population Growth

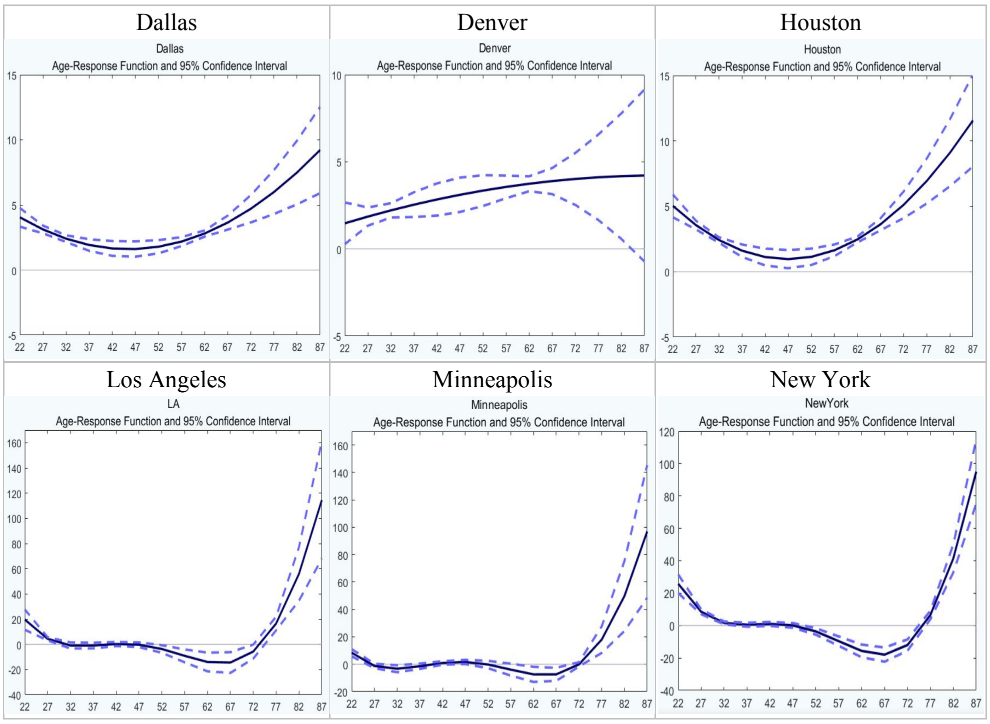
	Regional Per Capita Income Growth	Regional Population Growth
Atlanta	**-0.77****	0.02
	(0.34)	(1.88)
Baltimore	**-2.82*****	**-33.41****
	(0.83)	**(13.69)**
Boston	0.35	1.11
	(0.78)	(9.90)
Chicago	-0.53	**-12.43****
	(0.38)	**(5.99)**
Dallas	-0.32	2.28
	(0.27)	(1.47)
Denver	-0.51	0.17
	(0.34)	(1.90)
Detroit	**-0.95****	2.48
	(0.42)	(3.15)
Houston	-0.22	0.66
	(0.26)	(0.81)
Los Angeles	-0.54	**-19.98*****
	(0.60)	**(6.40)**
Miami	0.55	0.04
	(0.65)	(0.09)
Minneapolis	-0.03	**6.77***
	(0.41)	**(3.46)**
New York	-0.01	**-27.98*****
	(0.49)	**(4.25)**
Philadelphia	**-1.69*****	**14.91*****
	(0.41)	**(3.03)**
San Diego	**-2.19*****	**-6.04***
	(0.52)	**(3.06)**
San Francisco	-0.58	-6.68
	(0.66)	(4.68)
Seattle	**-0.72***	2.25
	(0.42)	(2.17)
St. Louis	-0.39	**10.93****
	(0.50)	**(5.23)**
Tampa	-0.20	**12.51*****
	(0.69)	**(3.32)**
Washington DC	-0.01	**-20.90****
	(0.78)	**(7.28)**

Note: Numbers in parentheses represent the standard errors. *, **, and *** denote that the coefficient is significant at the 10%, 5%, and 1% levels, respectively.



Note: This figure shows estimated age response functions which plotting impacts of each age group on the price-rent ratio.

Figure 1. Estimated Age Response Functions: Type 1



Note: This figure shows estimated age response functions which plotting impacts of each age group on the price-rent ratio.

Figure 2. Estimated Age Response Functions: Type 2

Given the differences in the shape of the age response functions, we determine whether these differences can be reconciled. We conjecture that differences in the age response functions may be associated with the degree of aging within the sampled areas. For example, the proportion of the population aged 60 or above in Dallas or Houston is approximately 16%, while that in Tampa is around 26%. When the relative size of the elderly population is low, the housing demand from the working age population can absorb the negative impact of the elderly population on house prices, which suggests that an increase in the proportion of the elderly population does not necessarily have a negative impact on house prices. However, when the size of the elderly population exceeds a certain threshold, its negative impact on house prices is more pronounced. As a result, the estimated age response function will be inverted U-shaped and exhibit negative coefficients for the elderly.

To investigate whether the shape of an estimated age response function (i.e., Type 1 or 2, as shown in Figures 1 and 2, respectively) is related to the degree of aging, we consider the following probit regression model:

$$ARF_i^* = a_0 + a_1 x_i + e_i, \quad (6)$$

where $e_i \sim N(0,1)$ and x_i denotes the degree of aging. As the degree of aging increases, the latent variable ARF_i^* is likely to exceed a certain threshold and the estimated age response functions tends to be inverted U-shaped (as in Figure 1), which is expressed as $ARF_i = 1$ in the probit regression. In contrast, when ARF_i^* is below the threshold, the estimated age response functions increase for the elderly population (as in Figure 2), which is expressed as $ARF_i = 0$. Thus, ARF_i is an indicator of the shape of an age response function. When the age response function is inverted U-shaped, i.e., Type 1 in Figure 1, ARF_i is set at 1. Otherwise, ARF_i is set at 0.[5]

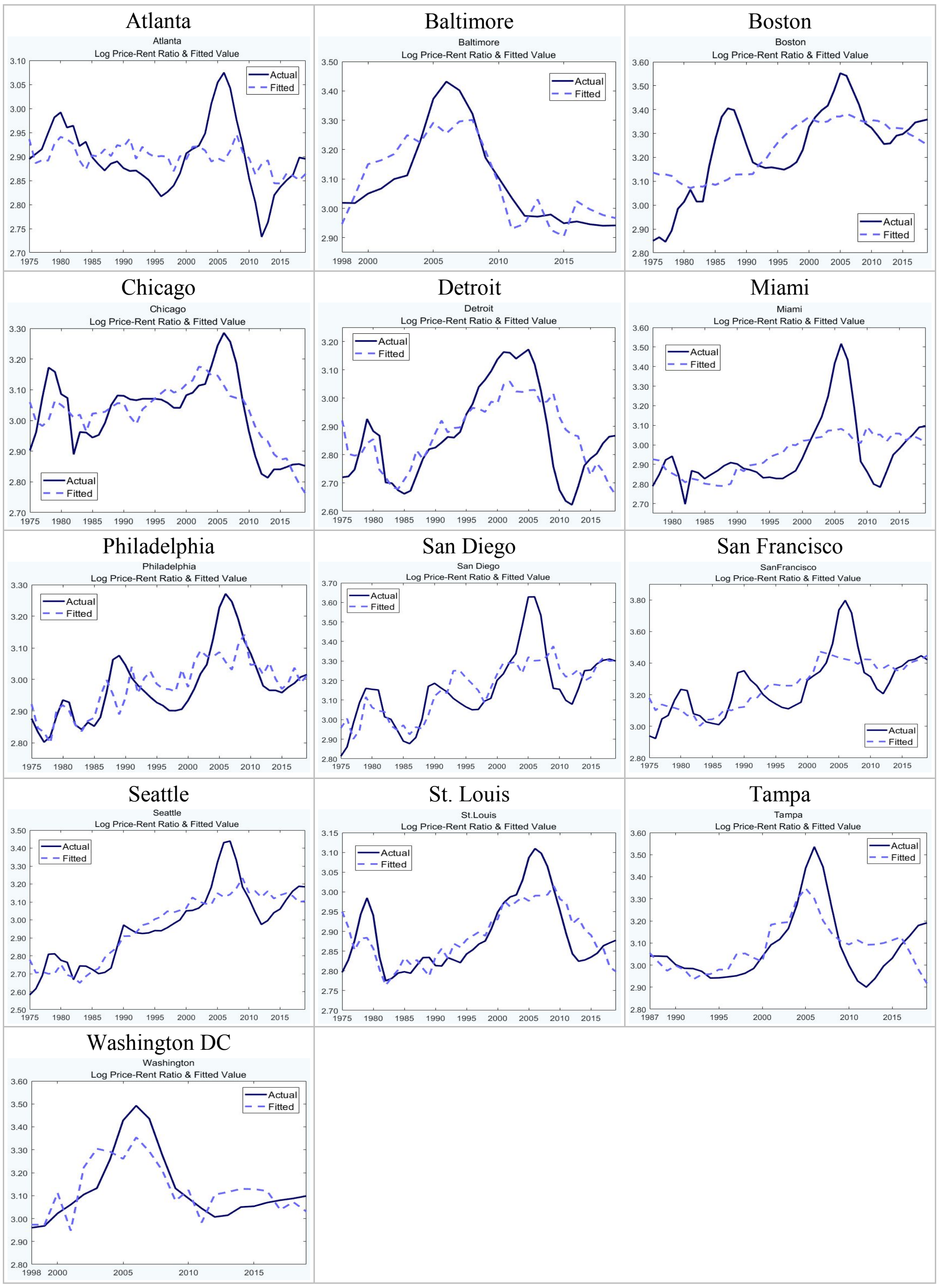
In the probit regression, x_i is the ratio of the population aged between 40 and 64 to the population aged 65 and above in 2019. As the population of a metropolitan area becomes more (less) aged, x_i will be lower (higher) and the shape of the age response function is more likely to be Type 1 (2), which implies that $ARF_i = 1\ (0)$.

Hence, if our conjecture is correct, then a_1 in Equation (6) will be negative. The results are presented in the first panel of Table 4. Although we have a small number of observations, a_1 is significantly negative at the 5% level, as shown in the first column. When we switch x_i to the ratio of the population aged between 20 and 64 to the population aged 65 and above in 2019, we can also obtain a significantly negative a_1, which is further supporting evidence for our conjecture. When we use the proportion of the population aged 60 or above in 2019 to measure the degree of aging, then x_i increases with the degree of aging. As a result, a_1 is positive under our conjecture, which is consistent with the results in the final column of the first panel in Table 4.[6]

We also conduct logit regression to check the robustness of the results from the probit regression. As shown in the second panel of Table 4, a_1 is significantly negative at the 10% level when x_i is the ratio of the population aged between 40 and 64 to the population aged 65 and above or the ratio of the population aged between 20 and 64 to the population aged 65 and above. a_1 also becomes significantly positive when x_i is the proportion of the population aged 60 or above.

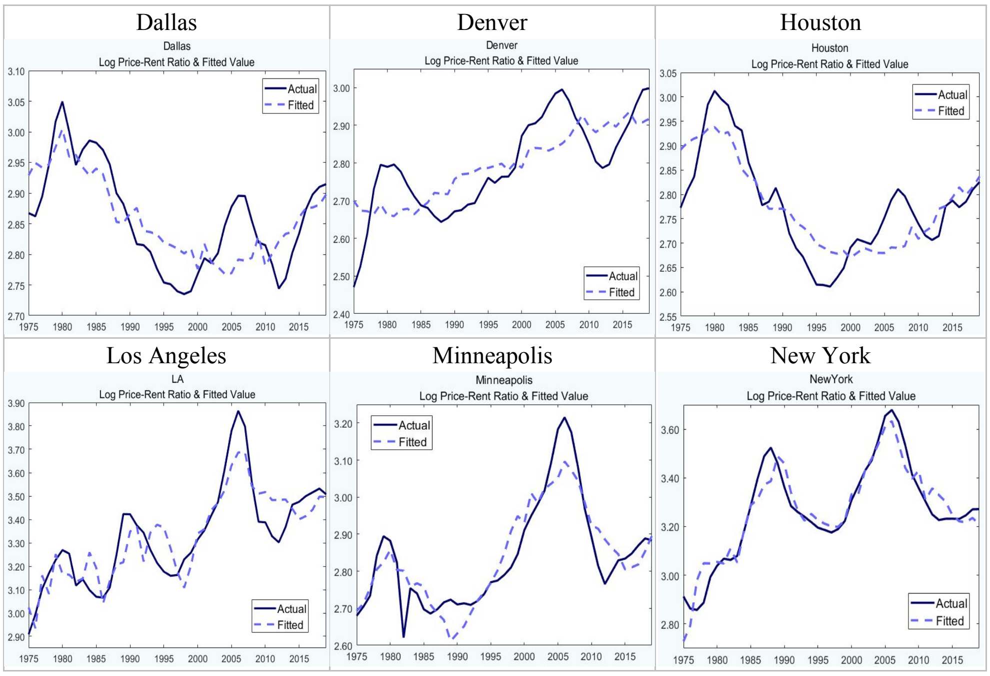
[5] Although a quadratic polynomial is chosen and the estimated coefficient of the quadratic term is negative for Denver, the estimated age response function increases for the elderly population. Hence, Denver is categorized as Type 2. The results of the probit regression in Table 4 are not significantly affected even when Denver is excluded from the regression analysis. These results are available upon request.

[6] Although quadratic polynomials are chosen and the estimated age response functions are inverted U-shaped, the coefficients of the age response function over the elderly population are positive in Atlanta, Philadelphia, and San Diego. Even if we exclude these areas from the regression analysis considering the discrepancy between the shape of the age response function and the sign of the coefficients over the elderly population, the regression results do not change qualitatively, and a_1 is robustly significant. These results are available upon request.



Note: This figure shows fitted values of price-rent ratio from semiparametric regression in Equation (2).

Figure 3. Fitted Values for Semiparametric Regression: Type 1



Note: This figure shows fitted values of price-rent ratio from semiparametric regression in Equation (2).

Figure 4. Fitted Values for Semiparametric Regression: Type 2

Table 4. Shape of the Age Response Functions and Aging Measures

	$ARF_i = \begin{cases} 1 & \text{for the age response functions in Figure 1} \\ 0 & \text{for the age response functions in Figure 2} \end{cases}$		
x_i	(40-64)/(65+)	(20-64)/(65+)	(60+)
	Probit regression		
a_0	6.2376** (2.6146) [0.017]	5.9137** (2.3245) [0.011]	-6.6392** (2.8701) [0.021]
a_1	-2.6129** (1.1836) [0.027]	-1.3025** (0.5409) [0.016]	34.3665** (13.9447) [0.014]
	Logit regression		
a_0	10.1376** (5.0682) [0.045]	9.7310** (4.7844) [0.042]	-10.8931* (5.9438) [0.067]
a_1	-4.2415* (2.2518) [0.060]	-2.1365* (1.1093) [0.054]	56.5204* (29.2391) [0.053]

Note: Numbers in parentheses represent the standard errors and the numbers in brackets are the p-values for H_0: $\alpha_i = 0$. *, and ** denote that the coefficient is significant at the 10% and 5% levels, respectively.

Overall, these results suggest that the shape of the age response function depends on the degree of aging and that, as the population of an economy becomes more aged, the shape of the age response function is more likely to be as shown in Figure 1, which is consistent with the life cycle hypothesis and the negative impact of aging on house prices.

5. CONCLUSION

We run semiparametric regressions for the price–rent ratio on the population age distribution for 19 metropolitan areas in the US to understand the impact of aging on house prices. Although many areas have an inverted U-shaped age response function, different series functions are selected and age response functions with different shapes are estimated between areas, which is consistent with the conflicting results reported in previous studies. Thus, the elderly generation has a negative impact on house prices in some metropolitan areas while they have a positive impact in other areas. We show that this difference in the shape of age response functions can be explained by the degree of aging in those areas. In particular, by conducting probit and logit regressions, we verify that the shape of the age response function is more likely to be inverted U-shaped as the population of a metropolitan area becomes more aged, which indicates that the shapes of the age response function are associated with the degree of aging. These results suggest that the impact of aging on house prices is negative eventually when an area becomes more aged.

Finally, changes in demographic structure may affect rents as well as house prices. Hence, our findings from probit and logit regressions may reflect different impacts of aging on rents and house prices. We think that the examination of differential impacts of aging on rents and house prices is an interesting future research topic.

REFERENCES

Andrews, D.K. (1991), "Asymptotic Normality of Series Estimators for Nonparametric and Semiparametric Regression Models," *Econometrica,* 59, 307-345.

Burman, P., E. Chow and D. Nolan (1994), "A Cross-validatory Method for Dependent Data," *Biometrika,* 81, 351-358.

Campbell, S.D., M.A. Davis, J. Gallin and R.F. Martin (2009), "What Moves Housing Markets: A Variance Decomposition of the Rent-price Ratio," *Journal of Urban Economics,* 66, 90-102.

Fair, R. C. and K. M. Dominguez (1991), “Effects of the Changing US Age Distribution on Macroeconomic Equations,” *American Economic Review,* 81, 1276-1294.
Gallant, A.R. (1981), “On the Basis in Flexible Functional Forms and an Essentially Unbiased Form: The Fourier Flexible Form,” *Journal of Econometrics,* 15, 211-245.
Green, R. and P.H. Hendershott (1996), “Age, Housing Demand, and Real House Prices,” *Regional Science and Urban Economics*, 26, 465-480.
Higgins, M. (1998), “Demography, National Savings, and International Capital Flows,” *International Economic Review,* 39, 343-369.
Hiller, N. and O.W. Lerbs (2016), “Aging and Urban House Prices,” *Regional Science and Urban Economics*, 60, 276-291.
Himmelberg, C., C. Mayer and T. Sinai (2005), “Assessing High House Prices: Bubbles, Fundamentals and Misperceptions,” *Journal of Economic Perspectives*, 19, 67-92.
Hort, K. (1998), “The Determinants of Urban House Price Fluctuations in Sweden 1968-1994,” *Journal of Housing Economics,* 7, 93-120.
Jäger, P. and T. Schmidt (2017), “Demographic Change and House Prices: Headwind or Tailwind?” *Economics Letters,* 160, 82-85.
Kishor, N.K. and J. Morley (2015), “What Factors Drive the Price-rent Ratio for the Housing Market? A Modified Present-value Analysis,” *Journal of Economic Dynamics and Control*, 58, 235-249.
Lisack, N., R. Sajedi and G. Thwaites (2017), “Demographic Trends and the Real Interest Rate,” Bank of England Working Papers No.701.
Mankiw, N.G. and D.N. Weil (1989), “The Baby Boom, the Baby Bust, and the Housing Market,” *Regional Science and Urban Economics,* 19, 235-258.
Park, C. (2010), “How does Changing Age Distribution Impact Stock Prices? A Nonparametric Approach,” *Journal of Applied Econometrics,* 25, 1155-1178.
Racine, J. (1997), “Feasible Cross-validatory Model Selection for General Stationary Processes,” *Journal of Applied Econometrics,* 12, 169-179.
Takáts, E. (2012), “Aging and House Prices,” *Journal of Housing Economics,* 21, 131-141.

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