Inequality, Demographics and the Housing Wealth Effect: Panel Quantile Regression Evidence for the US States

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Abstract

We extend the long-run Case, Quigley and Shiller (2013) type of specification on wealth effects by considering the role of inequality and demographics. Using a panel quantile framework for 48 US states, we find that higher levels of consumption lead to a larger (smaller) marginal effect of housing (financial) wealth. Both inequality and demographics affect consumption in a negative and significant way. Demographics are significant only for relative high levels of consumption.

Keywords: housing wealth, wealth effect, consumption, panel quantile, demographics, inequality.

JEL Classification: E21; G1; R31

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1 Introduction

Estimates of the stock market wealth effects are usually based in linear models, which relate the changes in average consumption to changes in average stock market wealth. The coefficient of the latter is typically found positive and significant. Similar estimates have been obtained for housing wealth (see Case *et al.*, 2005, henceforth CQS). CQS (2005) document an important effect of housing wealth on consumption in the US states, while stock market wealth is found to be positive but of lower importance. A similar picture emerges in the updated version of their study (see CQS, 2013), where the dataset is extended over time. A larger housing wealth effect is also reported by Calomiris *et al.* (2013), who also takes into account demographics and wealth distribution.

In this study we focus on the long-run effect of housing and financial wealth on consumption, contributing to the literature along three directions. First, given that the wealth estimates are prone to omitted variable bias, we assess the role of demographics and inequality on per capita consumption. Although the demographic structure has been explored by Calomiris *et al.* (2013), they rely only on interactions of the average population structure with other key variables to obtain their results. Instead, we explicitly include a measure of population structure that varies over time – albeit slowly. Second, measures of income inequality matter, as they may affect the borrowing constraints of individuals. Higher inequality is associated with higher wealth effects since low wealth individuals face more constraints on borrowing against permanent income. For instance, Mian and Sufi (2011) find that younger and low credit scores households, have stronger home equity-based borrowing, which could be used for consumption spending.[1] We take into account the effect of income inequality as measured by the Gini coefficient at the state level. Third, in contrast to the existing literature, we employ the panel quantile regression framework proposed by Canay (2011). By doing so, we can model the entire conditional

[1]See also Sinai and Souleles (2005) for a model in which, as result of borrowing constraints, housing wealth can affect consumption .

distribution of consumption. The latter allows us to relax the assumption of "symmetry" that the literature usually adopts, i.e. that the effect of wealth on consumption is the same with that on average consumption, and we evaluate the differential effects covariates have on low and high levels of consumption.

2 Data and methodology

Our dataset covers the period 1975:Q1 to 2012:Q2 and consists of real per capita consumption, personal income, financial wealth and housing wealth for the 48 contiguous US states — see CQS (2005; 2013).[2] We deflate each variable by the state–level seasonally adjusted CPI.[3] We also use the percentage of people over 65 and the state-level Gini obtained from the Census Bureau and Frank (2009), respectively.[4] We converted annual data to quarterly frequency by linear interpolation.

The original long-run specification in CQS (2005; 2013) is enriched in the spirit of Calomiris *et al.* (2013),[5] taking into account demographics and inequality. Allowing the coefficients to vary across quantiles (τ), the specification can be written as:

$$\begin{aligned} consumption_{i,t}^{(\tau)} &= \beta_0^{(\tau)} + \beta_1^{(\tau)} income_{i,t} + \beta_2^{(\tau)} fw_{i,t} + \beta_3^{(\tau)} hw_{i,t} + \beta_4^{(\tau)} over65_{i,t} \\ &\quad + \beta_5^{(\tau)} Gini_{i,t} + \alpha_i + \epsilon_{i,t} \end{aligned} \tag{1}$$

where $consumption_{i,t}$ is (log) real per capita consumption in state i at time t, $income_{i,t}$ is (log) real per capita personal income, $fw_{i,t}$ is (log) real per capita financial wealth, $hw_{i,t}$ is (log) real per capita housing wealth, $over65_{i,t}$ is the percentage of population over 65 years old, $Gini_{i,t}$ is the Gini coefficient, α_i denotes state-level fixed effects and $\epsilon_{i,t}$ is a

[2]We are grateful to Karl Case for making these data available to us. For a detailed description of the data see Case *et al.* (2005).

[3]We employ the U.S. City Average, for various geographic areas (regions and metropolitan areas), provided by BLS. See: `http://www.bls.gov/eag/abouteag.htm`

[4]The data are available at `http://www.shsu.edu/eco_mwf/inequality.html`.

[5]This model is in the spirit of Table 3 (page 117) in CQS (2013). The quantile regression results for the CQS specification ($\beta_4 = \beta_5 = 0$) are available on an online Appendix.

disturbance term. To avoid simultaneity issues, the variables $over65_{i,t}$ and $gini_{i,t}$ are the values observed in the previous year.

We extend the existing literature, by relaxing the symmetry assumption (e.g. estimates of $\beta_k^{(\tau)}$ for a range of $\tau = 0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95$ and $k = 0, 1, 2, 3, 4, 5$) as we adopt the two-step a panel quantile regression framework of Canay (2011) for Equation (1).[6]

3 Empirical results

Table 1 presents the results from the fixed-effects estimators. Income, financial wealth and housing wealth, all affect consumption in a positive and significant way. On the other hand demographics (% of people with age 65+) and inequality have a negative and significant effect on consumption, on average. Note here that the effect of housing wealth is stronger than that of financial wealth.[7]

We proceed by employing quantile regression techniques, which allow $\beta_j^{(\tau)}$ to vary at different quantiles, τ. Table 2 presents our estimation results using the two-step estimator of Canay (2011) for the 48 states.[8] At the lower end of the conditional distribution of consumption ($\tau = 0.05$ and $\tau = 0.10$) both fw and hw are statistically significant and of similar size (between 0.053 and 0.088). Demographics are not while the *gini* coefficient is negative and significant. Note that *gini*'s coefficient remains significant at the 1% level throughout the conditional distribution of consumption. As we move to higher quantiles the effect of income and hw is increasing and the effect of fw is decreasing. At higher quantiles the coefficient of hw is at least two times that of fw. The coefficients of the demographics variable becomes significant from $\tau = 0.20$ onwards and seems to become

[6]Canay (2011) provides sufficient conditions under which the parameter of interest is identified for fixed T and demonstrates that through a simple transformation of the data that eliminates the fixed effects as $T \to \infty$, the fixed effects can then be viewed as location shift variables (i.e. variables that affect all quantiles in the same way).

[7]CQS assume that $\beta_4 = \beta_5 = 0$ and estimate $\hat{\beta}_1 = 0.55$, $\hat{\beta}_2 = 0.075$ and $\hat{\beta}_3 = 0.18$.

[8]Results for all 50 states (plus Washington DC) are available in an online appendix.

Table 1: Wealth Effects - dependent variable: consumption

	FE	FE with Driscoll-Kraay S.E.
(intercept)	1.228***	1.228***
	(0.089)	(0.482)
income	0.625***	0.625***
	(0.011)	(0.057)
fw	0.050***	0.050***
	(0.002)	(0.008)
hw	0.082***	0.082***
	(0.004)	(0.010)
65+	-0.534***	-0.534**
	(0.085)	(0.251)
Gini	-0.794***	-0.794***
	(0.029)	(0.158)
R^2 within	0.796	0.796

Notes: Standard errors in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. FE denotes Fixed Effects.

more negative as we move to the right tail of the conditional distribution. The latter suggests that when consumption is relatively high demographics affect consumption in an increasingly negative way. Figure 1 depicts the coefficients per quantile against a fixed effect estimator and the CQS (2013) estimate for comparison purposes. The FE coefficients and the CQS (2013) estimate of income seem to be very close to the median QR response ($\tau = 0.5$). The CQS (2013) fw estimate is close to the upper bound of the QR confidence interval estimate. The former is two times the latter in the case of hw. The demographics (inequality) coefficient has a downward trend (U shape) (see Figure 1).[9].

[9]As a robustness exercise, we add three states (Hawai, Alaska and DC) and re-run the models. The results for the 51 states confirm our previous findings (additional robustness analysis is available on the online Appendix)

Table 2: Quantile regression, Wealth Effects (48 states) - dependent variable: consumption

Quantiles	(intercept)	income	fw	hw	65+	gini
$\tau = 0.05$	1.170***	0.612***	0.053***	0.071***	-0.127	-0.668***
	(0.453)	(0.057)	(0.017)	(0.025)	(0.262)	(0.138)
$\tau = 0.10$	1.247***	0.605***	0.054***	0.088***	-0.252	-0.749***
	(0.330)	(0.043)	(0.013)	(0.017)	(0.234)	(0.096)
$\tau = 0.20$	1.130***	0.627***	0.050***	0.091***	-0.389	-0.803***
	(0.258)	(0.034)	(0.011)	(0.013)	(0.242)	(0.086)
$\tau = 0.30$	1.089***	0.637***	0.050***	0.087***	-0.437**	-0.842***
	(0.241)	(0.032)	(0.010)	(0.012)	(0.218)	(0.078)
$\tau = 0.40$	1.053***	0.646***	0.050***	0.082***	-0.488***	-0.880***
	(0.211)	(0.028)	(0.008)	(0.013)	(0.199)	(0.083)
$\tau = 0.50$	1.012***	0.657***	0.048***	0.078***	-0.536***	-0.887***
	(0.218)	(0.029)	(0.008)	(0.013)	(0.176)	(0.087)
$\tau = 0.60$	1.032***	0.657***	0.047***	0.078***	-0.627***	-0.880***
	(0.227)	(0.031)	(0.008)	(0.015)	(0.170)	(0.082)
$\tau = 0.70$	1.098***	0.649***	0.046***	0.086***	-0.721***	-0.844***
	(0.234)	(0.032)	(0.009)	(0.017)	(0.171)	(0.083)
$\tau = 0.80$	1.220***	0.633***	0.047***	0.096***	-0.803***	-0.800***
	(0.251)	(0.035)	(0.010)	(0.018)	(0.173)	(0.094)
$\tau = 0.90$	1.342***	0.616***	0.046***	0.110***	-0.844***	-0.741***
	(0.265)	(0.036)	(0.012)	(0.021)	(0.192)	(0.102)
$\tau = 0.95$	1.443***	0.606***	0.047***	0.110***	-0.841***	-0.711***
	(0.287)	(0.038)	(0.014)	(0.025)	(0.198)	(0.110)

Notes: Each pair of rows reports the coefficient estimate and the associated bootstrap standard error in parenthesis for each quantile (τ). The bootstrap standard error has been obtained using 1000 replications. ***, ** and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

4 Conclusions

This paper examines the long-run effects of housing and financial wealth on consumption, employing data for a panel of 48 US states from 1975:Q1 to 2012:Q2. Our contribution is threefold: (i) we allow the population structure to play a differential role in shaping aggregate per-capita consumption patterns, (ii) we augment the model by considering per state *gini* coefficients (iii) all the above are estimated within a panel quantile regression framework that allows for fixed effects and relaxes the assumption of symmetry. We find that the housing wealth effect is larger than the financial wealth effect, in line with pre-

vious empirical evidence (except for $\tau = 0.05$). This difference widens as we move to higher values of consumption; for relative high levels of income, housing wealth has a coefficient two time that of financial wealth. Moreover, we find that a larger percentage of people over 65 years of age and a higher degree of income inequality (as measured by the Gini coefficient), also lead to lower consumption in the long-run.

Acknowledgments

The authors are grateful to Karl Case for making the data available. The usual caveat applies.

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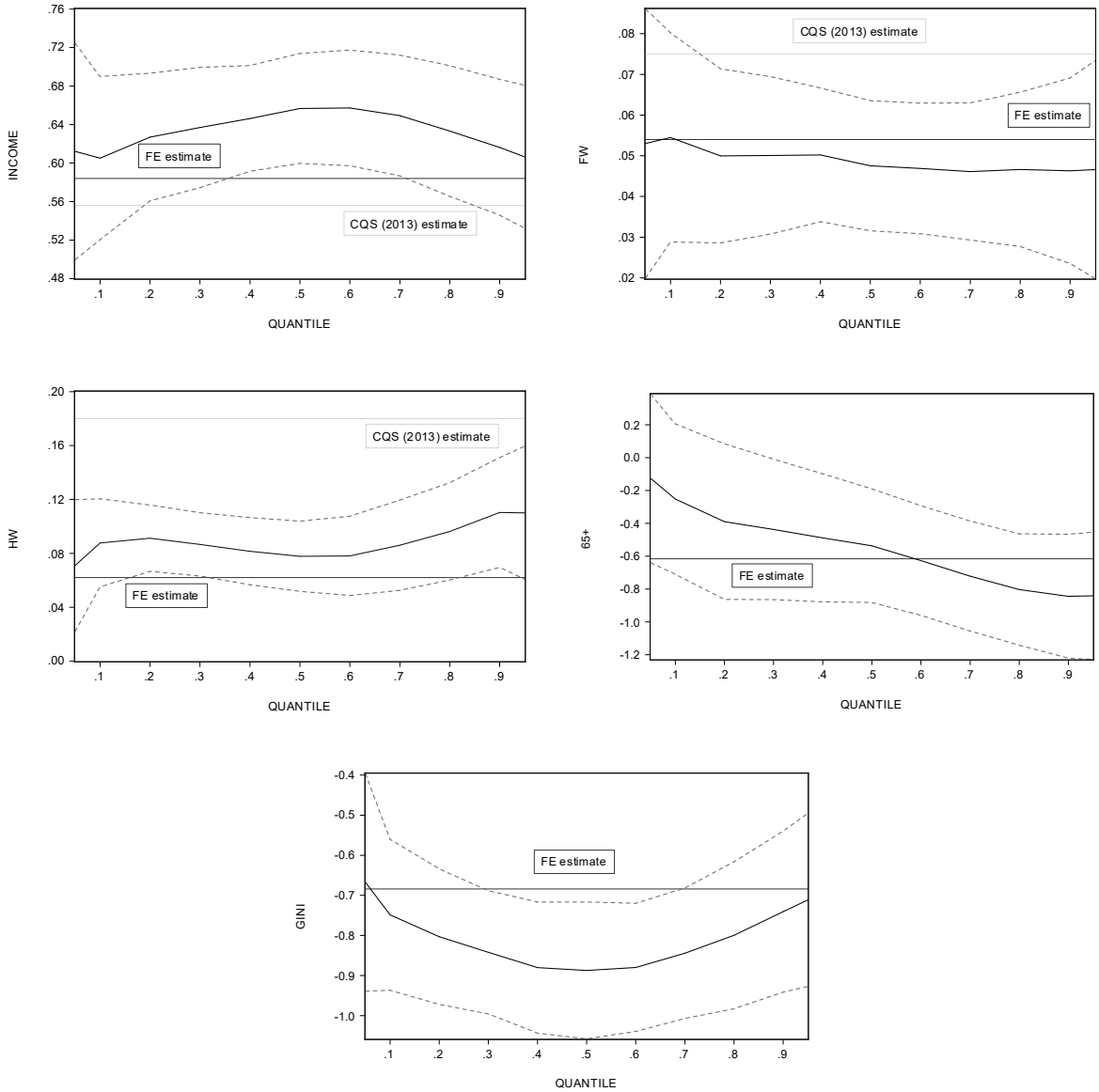

Figure 1: Quantile fixed effect coefficient estimates for 48 US states

Appendix

Table 1: Wealth Effects - dependent variable: consumption

	FE		FE with Driscoll-Kraay s.e.	
	51 states	48 states	51 states	48 states
(intercept)	1.609***	1.228***	1.609***	1.228***
	(0.082)	(0.089)	(0.411)	(0.482)
income	0.584***	0.625***	0.584***	0.625***
	(0.010)	(0.011)	(0.047)	(0.057)
fw	0.054***	0.050***	0.054***	0.050***
	(0.002)	(0.002)	(0.008)	(0.008)
hw	0.062***	0.082***	0.062***	0.082***
	(0.004)	(0.004)	(0.009)	(0.010)
65+	-0.616***	-0.534***	-0.616***	-0.534**
	(0.078)	(0.085)	(0.238)	(0.251)
Gini	-0.684***	-0.794***	-0.684***	-0.794***
	(0.027)	(0.029)	(0.143)	(0.158)
RMSE	0.058	0.057		
R^2 within	0.782	0.796	0.782	0.796
R^2 between	0.115	0.145		
R^2 overall	0.2230	0.252		

Notes: Standard errors in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. FE denotes Fixed Effects and CCE denotes Common Correlated Effects. RMSE is root mean squared error.

Table 2: Quantile regression, Wealth Effects (51 states) - dependent variable: consumption

Quantiles		(intercept)	income	fw	hw	65+	gini
τ=0.05	estimate	1.736***	0.547***	0.059***	0.057***	-0.219	-0.521***
	Boot SE	0.365	0.048	0.015	0.021	0.221	0.125
τ=0.10	estimate	1.713***	0.554***	0.058***	0.070***	-0.313	-0.611***
	Boot SE	0.302	0.040	0.013	0.015	0.239	0.103
τ=0.20	estimate	1.549***	0.581***	0.056***	0.073***	-0.548**	-0.678***
	Boot SE	0.300	0.039	0.012	0.013	0.236	0.084
τ=0.30	estimate	1.555***	0.583***	0.057***	0.072***	-0.563***	-0.717***
	Boot SE	0.286	0.036	0.012	0.011	0.202	0.086
τ=0.40	estimate	1.517***	0.592***	0.057***	0.069***	-0.566***	-0.756***
	Boot SE	0.255	0.032	0.010	0.011	0.180	0.085
τ=0.50	estimate	1.447***	0.605***	0.054***	0.065***	-0.612***	-0.763***
	Boot SE	0.248	0.031	0.009	0.012	0.152	0.084
τ=0.60	estimate	1.437***	0.610***	0.051***	0.066***	-0.659***	-0.753***
	Boot SE	0.228	0.030	0.009	0.013	0.140	0.079
τ=0.70	estimate	1.487***	0.608***	0.049***	0.068***	-0.705***	-0.738***
	Boot SE	0.240	0.032	0.009	0.015	0.144	0.086
τ=0.80	estimate	1.542***	0.602***	0.048***	0.074***	-0.815***	-0.690***
	Boot SE	0.251	0.034	0.010	0.019	0.166	0.099
τ=0.90	estimate	1.592***	0.597***	0.047***	0.078***	-0.924***	-0.622***
	Boot SE	0.275	0.038	0.012	0.023	0.158	0.111
τ=0.95	estimate	1.605***	0.598***	0.048***	0.072***	-0.863***	-0.640***
	Boot SE	0.344	0.048	0.014	0.036	0.191	0.128

Notes: Boot SE denote the bootstrap standard errors for 1000 bootstrap replicates. ***, ** and * denote statistical significance at 1%, 5% and 10% significance levels, respectively.

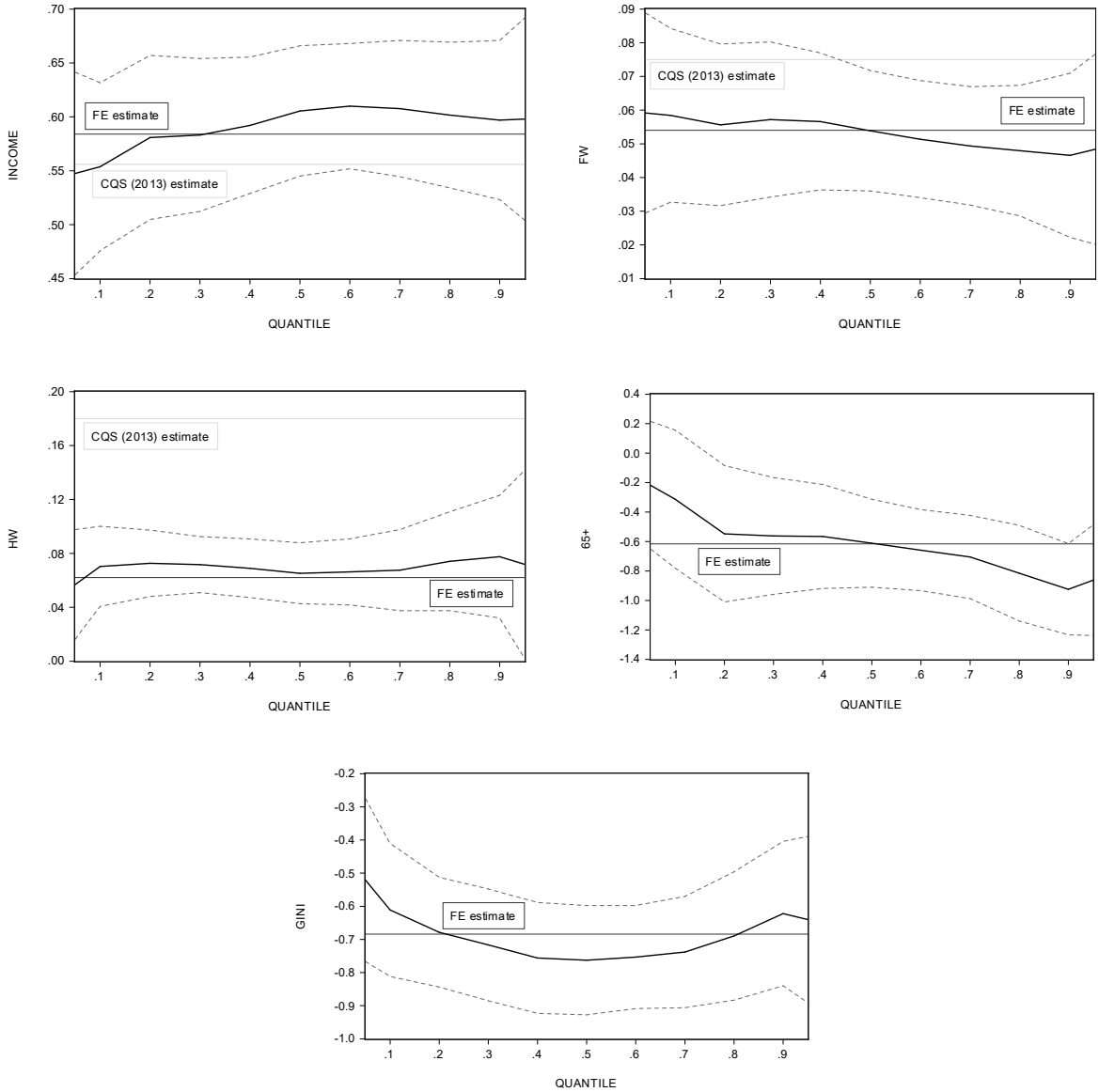

Figure 1: Quantile fixed effect coefficient estimates for 51 US states