TREATMENT EFFECTS CONTINUED FROM LECTURE 13

We now turn to the effect of participation in 401(k) on net total financial assets. Tables 2 and 3 report estimates of the LATE and LATT. The first row of each panel report estimates from the linear instrumental variables method of [5] that imposes a constant treatment effect. The second and third row in each panel use the doubly robust approach for LATE of Section 4 with the parametrizations

$$\mu_z(X, \beta_z) = f(X)'\beta_z, \quad q_z(X, \lambda_z) = \Lambda(f(X)'\lambda_z), \quad \text{and } p_z(X, \ell_z) = \Lambda(f(X)'\ell_z),$$

where we consider the same specifications for $f(X)$ as above. Again, β_0 and β_1 are estimated by least squares, and λ_0, λ_1 and ℓ_1 are estimated by logit regression in table 4, whereas they are estimated by the Lasso version of the same methods in table 5.[8]

TABLE 4. Local Average Treatment Effects of p401 on net_tfa

	Est.	Std. Error	95% LCI	95% UCI
A - Without interactions (25 controls)				
IV	12,939	1,731	9,547	16,331
LATE	9,201	2,907	3,503	14,899
LATT	15,951	2,157	11,722	20,179
B - With two-way interactions (275 controls)				
IV	12,922	1,567	9,850	15,994
LATE	134,769	529,304	-902,648	1,172,186
LATT	1,317,808	1,057,078	-754,026	3,389,642

The comparison between tables 4 and 5 is similar to the comparison of tables 2 and 3. Thus, the methods that do not select controls produce very imprecise estimates of the LATE and LATT in the specification with interactions. The selection of controls using Lasso regularizes the estimates and produces estimates that are more stable across specifications. Controlling for observed and unobserved heterogeneity reduces the LATE by more than half with respect to the APE of p401. IV produces estimates in between the LATE and LATT. A comparison between the LATE and LATT suggests the presence of heterogeneity in the average effects for treated and non treated compliers, but this evidence is not statistically significant at the 5% level. Based on the estimates with selection of controls, the local average effect of 401 participation is between $9,200$ and $11,600$, increasing to around $15,600 - 16,000$ for the treated.

Figures 3 and 4 report estimates and 95% confidence bands for the LQTE and LQTT functions of p401. They are constructed from estimates and confidence bands of distributions of potential outcomes using the method described in L7. The distributions are

[8]Note that we do not need to estimate ℓ_0 because $p_0(X, \ell_0) = 1 - p_1(X, \ell_1)$.

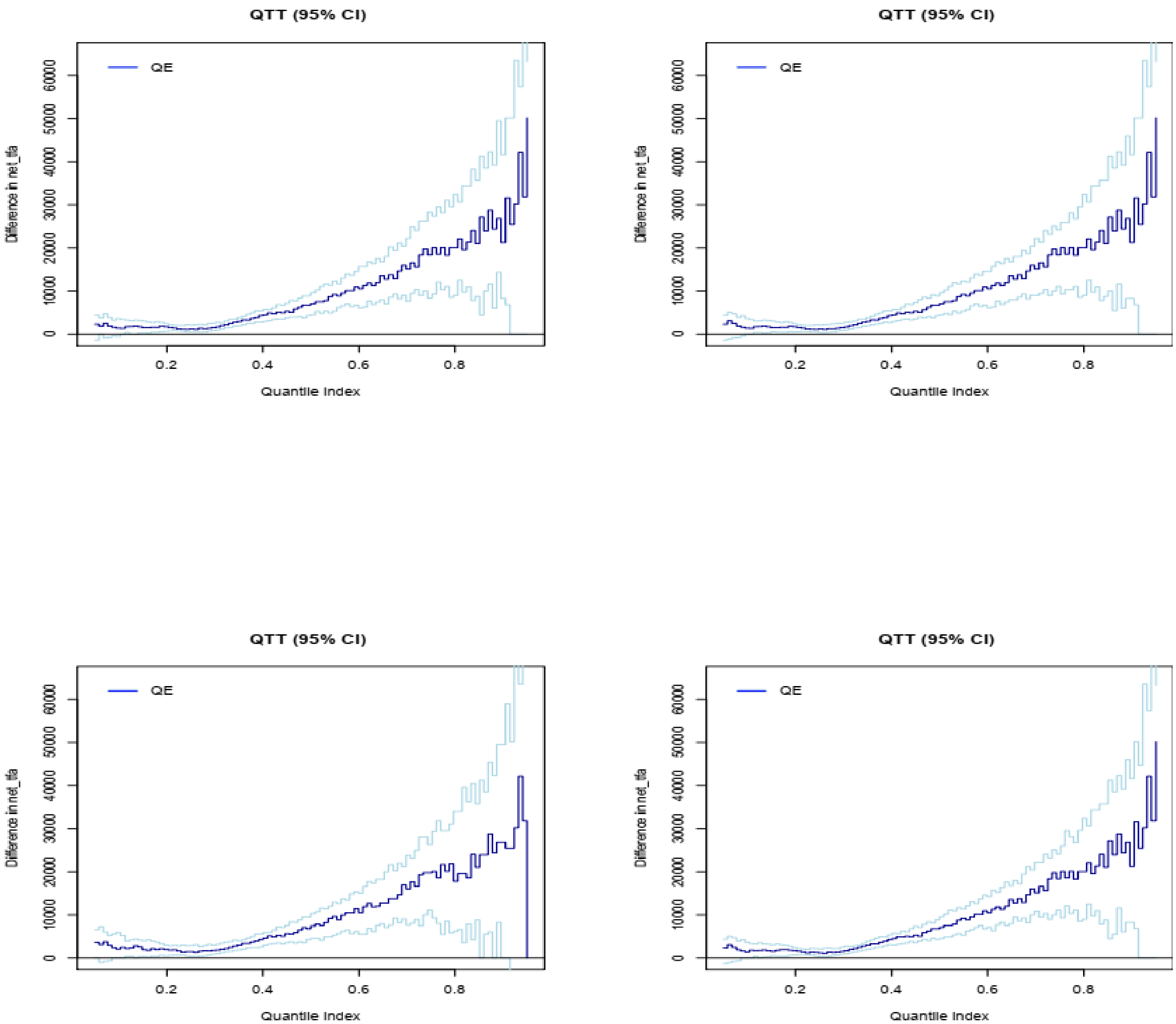

FIGURE 2. Quantile treatment effects of e401 on net_tfa. Panels differ in the specification of $f(X)$ and the estimation method. Upper-left: specification without interactions and no selection of controls. Upper-right: specification without interactions and selection of controls by Lasso. Lower-left: specification with two-way interactions and no selection of controls. Lower-right: specification with two-way interactions and selection of controls by Lasso. Conditional distribution and propensity estimated by logit regression. 95% confidence bands obtained by inversion of 95% joint confidence bands for distributions.

TABLE 5. Local Average Treatment Effects of e401 on net_tfa with Selection of Controls

	Est.	Std. Error	95% LCI	95% UCI
A - Without interactions (25 controls)				
IV	12,312	1,788	8,809	15,816
LATE	11,638	1,583	8,536	14,741
LATT	15,947	2,186	11,664	20,231
B - With two-way interactions (275 controls)				
IV	12,022	1,811	8,472	15,571
LATE	11,568	1,607	8,418	14,717
LATT	15,640	2,220	11,289	19,990

estimated using the doubly robust approach of Section 4 with the parametrizations

$$p_z(X, \ell_d) = \Lambda(f(X)'\ell_z), \ \mu_{z,d,y}(X, \beta_{z,d,y}) = \Lambda(f(X)'\beta_{z,d,y}), \ q_{z,d}(X, \lambda_{z,d}) = \Lambda(f(X)'\lambda_{z,d}),$$

where we consider the same specifications for $f(X)$ as above. We estimate all the parameters by logit regressions with and without Lasso selection of controls. The confidence bands are obtained by multiplier bootstrap with 200 and Mammen multipliers.

We find again that the selection-based estimates of local average effects are stable across specifications and are very similar to the estimates obtained without selection from the specification without interactions. If we focus on the LQTE and LQTT estimated from variable selection methods, we find that 401(k) participation has a small impact on accumulated net total financial assets at low quantiles while appearing to have a larger impact at high quantiles for compliers. Looking at the uniform confidence intervals, we can see that this pattern is statistically significant at the 5% level and that we would reject the hypothesis that the effect of 401(k) participation on net total financial assets is constant across the distribution.

APPENDIX A. TREATMENT EFFECTS ON THE TREATED

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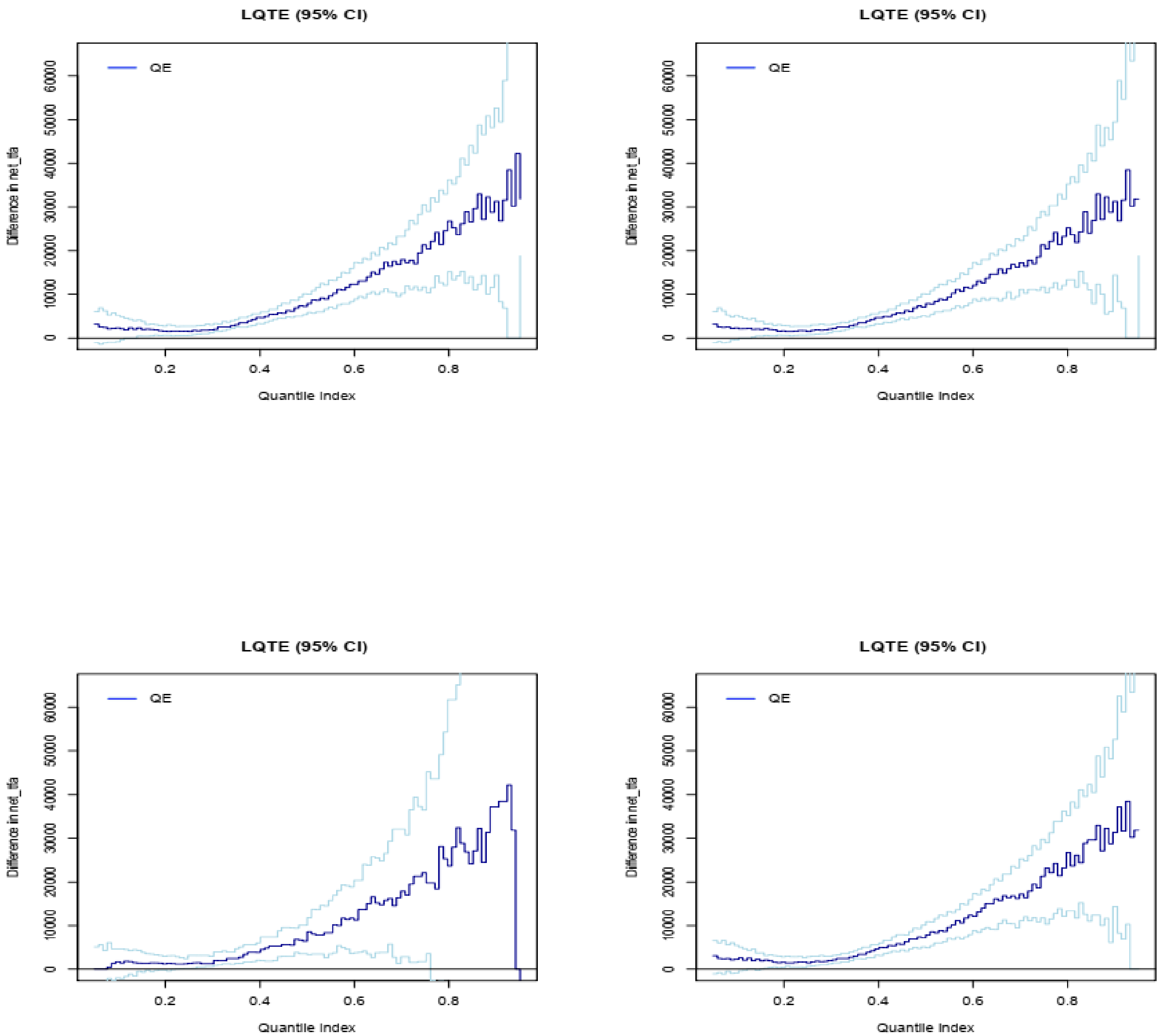

FIGURE 3. Local quantile treatment effects of p401 on net_tfa. Panels differ in the specification of $f(X)$ and the estimation method. Upper-left: specification without interactions and no selection of controls. Upper-right: specification without interactions and selection of controls by Lasso. Lower-left: specification with two-way interactions and no selection of controls. Lower-right: specification with two-way interactions and selection of controls by Lasso. Conditional distribution and propensity estimated by logit regression. 95% confidence bands obtained by inversion of 95% joint confidence bands for distributions.

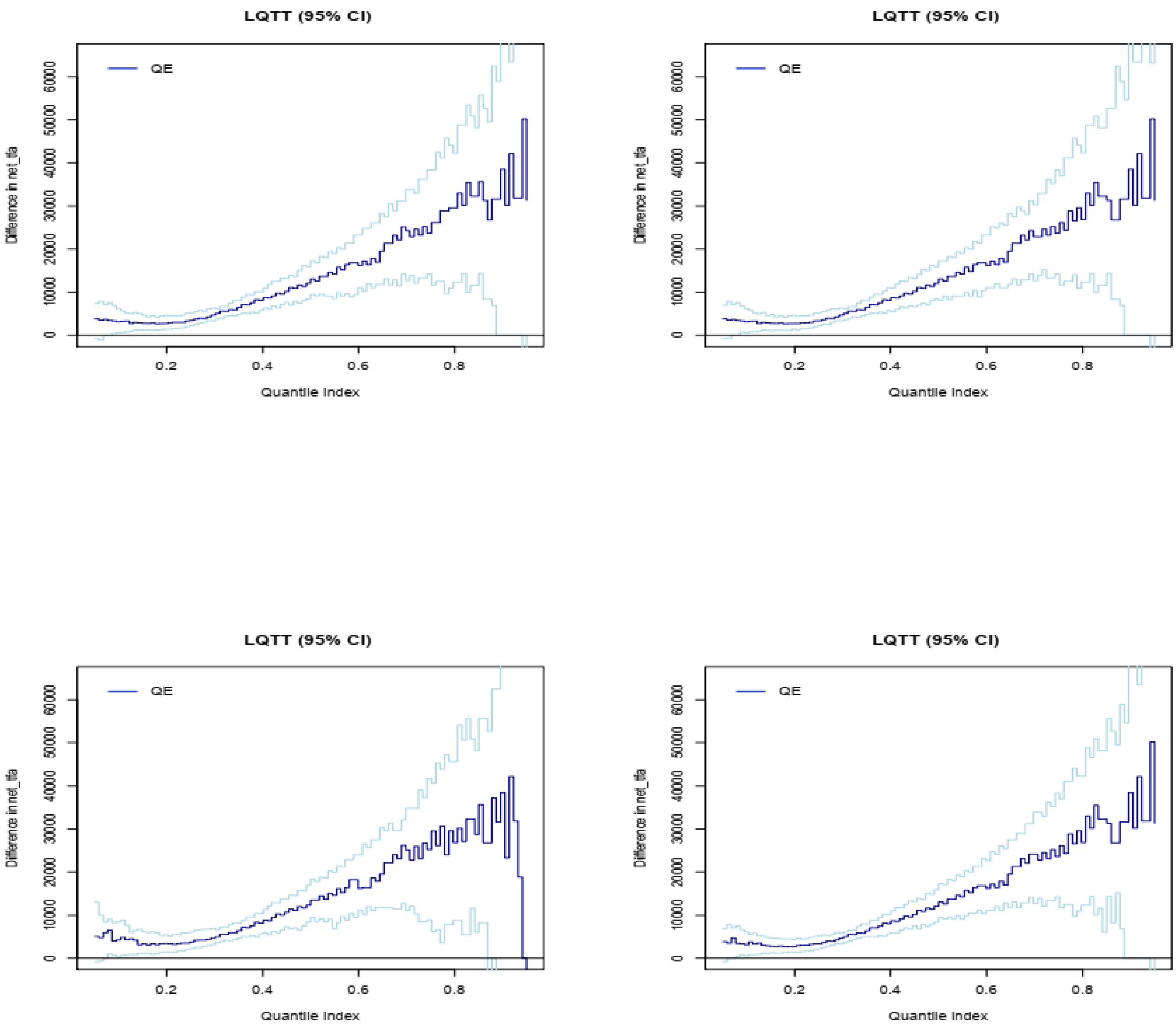

FIGURE 4. Local quantile treatment effects on the treated of p401 on net_tfa. Panels differ in the specification of $f(X)$ and the estimation method. Upper-left: specification without interactions and no selection of controls. Upper-right: specification without interactions and selection of controls by Lasso. Lower-left: specification with two-way interactions and no selection of controls. Lower-right: specification with two-way interactions and selection of controls by Lasso. Conditional distribution and propensity estimated by logit regression. 95% confidence bands obtained by inversion of 95% joint confidence bands for distributions.

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