XVIII*th* International Conference on Cultural Economics, Montreal, 2014

Decomposition analysis of returns from non-standard investment markets:

Why selling Picasso in New York is different

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Outline of the presentation

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Motivation

Limits of the LOP

- The Law of One Price (LOP) say that identical assets must have identical prices → arbitrage
- Serious doubts arise about the validity of the LOP in the markets for non-standard investments:
  - No identical goods
  - Presence of risk
  - It could be no possible to resale goods
- In the art market there is evidence that the arbitrage does not necessarily equalize prices (Pesando, 1993; Renneboog and Van Houtte, 2002; Forsund and Zanola, 2007; among the others)

Motivation

Aim

- To analyze why the distribution of prices differ across New York (NY) and the Rest of World (RoW). To this aim two different questions arise:
  - Does the distribution change because items sold in NY have different characteristics than items sold in the RoW?
  - Is the distributional change unrelated to item characteristics, and has caused differences in the hedonic price functions across markets?

- Based on the unconditional Recentered Influence Function (RIF) regression method based on Firpo et al. (2007, 2009), we decompose price distribution across different markets

Method

Beyond Oaxaca decomposition

- The Oaxaca-Blinder decomposition is widely used to decompose average price gap between two groups into an effect explained by the differences in covariates and an unexplained effect due to the different returns to covariates.

- However, the simple mean Oaxaca-Blinder comparisons are not necessarily informative about developments in the upper tail of the price distribution (Etilé, 2011; Johar et al.)

  - *Conditional quantile regression:* to assess the impact of a covariate on quantile of the outcome conditional on a specific values of other covariates → Cons: a change in the distribution of covariates may change the interpretation of the coefficients estimates
  - ***Unconditional quantile regression***: Firpo et al. (2007, 2009)

Method

Firpo et al. (2007, 2009)

- The Firpo et al. (2007, 2009) decomposition method is based on two steps:
  - First step: to estimate the unconditional Recentered Influence Function (RIF) regression to primarily investigate the differences across quantiles in the distribution of returns
  - Second step: based on quantile RIF-regressions, we decompose price distributions across different markets

Method

First step: RIF-regression

- The Firpo et al. (2009) replaces the original dependent variable of a standard hedonic regression (Y_{ij}) with a simple transformation known as RIF. The Recentered Inluence Function (RIF) for the quantile q_τ is

$$RIF\left(Y;q_\tau\right)=q_\tau+\frac{\tau-I\left(Y\leq q_\tau\right)}{f_Y\left(q_\tau\right)}$$

where f_Y is the marginal density function of Y, and I is an indicator function.

- Since the RIF is unobserved in practice, we use its sample analog that replace the unknown quantities by their estimators

$$RIF\left(Y;\hat{q}_\tau\right)=\hat{q}_\tau+\frac{\tau-I\left(Y\leq \hat{q}_\tau\right)}{\hat{f}_Y\left(q_\tau\right)}$$

where $\hat{q}_\tau$ is the τth sample quantile and $\hat{f}_Y$ is the kernel density estimator.

Method

Second step: RIF-based decomposition

- The distributional statistic of interest can be written in terms of expectations of its conditional RIF

$$q_{g,\tau} = \mathrm{E}_X\left[\mathrm{E}\left[RIF\left(Y_g;\hat{q}_{g,\tau}\right)\middle| X_g\right]\right] = \mathrm{E}\left[X_g\right]\hat{\gamma}_{g,\tau}$$

where $q_{g,\tau}$ is the unconditional τth sample quantile for group $g \in \{NY, RoW;\}$ X is a vector of covariates; and $\hat{\gamma}_{g,\tau}$ is the coefficient of the unconditional quantile regression.

- From which it follows:

$$\underbrace{\left[RIF\left(Y_{NY},\hat{q}_{NY,\tau}\right)\right]-\left[RIF\left(Y_{R0W},\hat{q}_{RoW,\tau}\right)\right]}_{\hat{\Delta}_{NY,\tau}}=$$

$$\underbrace{\left(\overline{X}_{NY}-\overline{X}_{RoW}\right)\beta_{NY,\tau}}_{\hat{\Delta}_{X,\tau}}+\underbrace{\left(\beta_{NY}-\beta_{RoW}\right)\overline{X}_{NY,\tau}}_{\hat{\Delta}_{\beta,\tau}}$$

Explained (composition effect) **Unexplained (structural effect)**

Decomposition results
Data

- 974 Picasso paintings sold at auction worldwide during the period 1990-2010 (Art Price)

- List of variables: artist's name, nationality, title of the work, year of production, materials used, date and city of sale, auction price, dimensions, signature, and a number of further information that might vary from case to case.

- Dataset completed with a series of indicators about the artistic styles of the painting

- Nominal USD prices are deflated using US CPI prices (2000=100)

Decomposition results

Data

	Mean	Description
price	2,732,559	price of paintings (Euros, 2000=100)
size	.626	area (m2)
panel	.085	oil on panel
canvas	.712	oil on canvas
mixed	.039	mixed media
other_med	.0249	other media (omitted category)
ny	.544	sold in New York
world	.456	sold in the rest of the world (omitted category)
sotheby	.424	sold at Sotheby's
christie	.442	sold at Christie's
other_auc	.134	sold at other auction houses (omitted category)
style1	.050	Childhood and Youth (1881-1901)
style2	.018	Blue and Rose Period (1902-1906)
style3	.050	Analytical and Synthetic Cubism (1907-1915)
style4	.100	Camera and Classicism (1916-1924)
style5	.094	Juggler of the Form (1925-1936)
style6	.135	Guernica and 'Style Picasso' (1937-1943)
style7	.133	Politics and Art (1944-1953)
style8	.223	The Old Picasso (1954-1973) (omitted category)

Decomposition results

Unconditional quantile RIF-regression results

	25th quantile		50th quantile		75th quantile		90th quantile	
	Coef.	Bootstrap Std. Err.	Coef.	Bootstrap Std. Err.	Coef.	Bootstrap Std. Err.	Coef.	Bootstrap Std. Err.
size	.142*	.087	.423***	.166	.592***	.158	.650***	.142
panel	1.199***	.265	.765***	.275	.464*	.253	.717***	.283
canvas	1.280***	.204	1.132***	.180	.932***	.167	.732***	.175
mixed	-1.013***	.381	-.378	.301	.115	.287	.380*	.223
ny	.305***	.109	.256**	.125	.411***	.139	.515***	.137
sotheby	.212	.245	.301	.192	.411**	.175	-.260	.183
christie	.240	.245	.265	.204	.201	.176	.009	.177
style1	.334	.302	1.206***	.287	1.182***	.363	.718**	.310
style2	.767**	.364	.809**	.396	2.207***	.510	3.368***	.930
style3	.495*	.276	.819***	.310	1.117***	.336	1.382***	.930
style4	-.283	.186	-.181	.213	.093	.225	.389*	.238
style5	.495***	.178	.774***	.212	1.122***	.261	1.111***	.361
style6	.307**	.151	.933***	.197	1.072***	.229	.438**	.215
style7	-.183	.170	.078	.174	.248	.196	-.067	1.69
constant	10.739***	.426	10.977***	.402	12.105***	.420	13.799***	.373
Time d.	[incl.]		[incl.]		[incl.]		[incl.]	
F	12.19		12.38		9.00		4.16	
Prob > F	.000		.000		.000		.000	
Adj R^2	.23		.27		.23		.17	

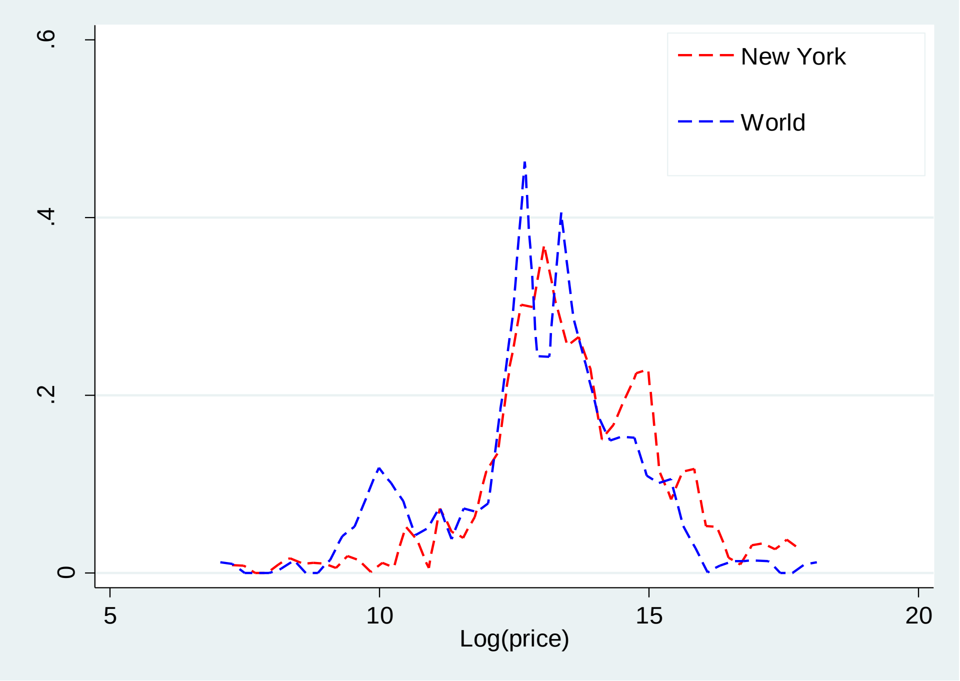
Decomposition results

Decomposition analysis: full sample

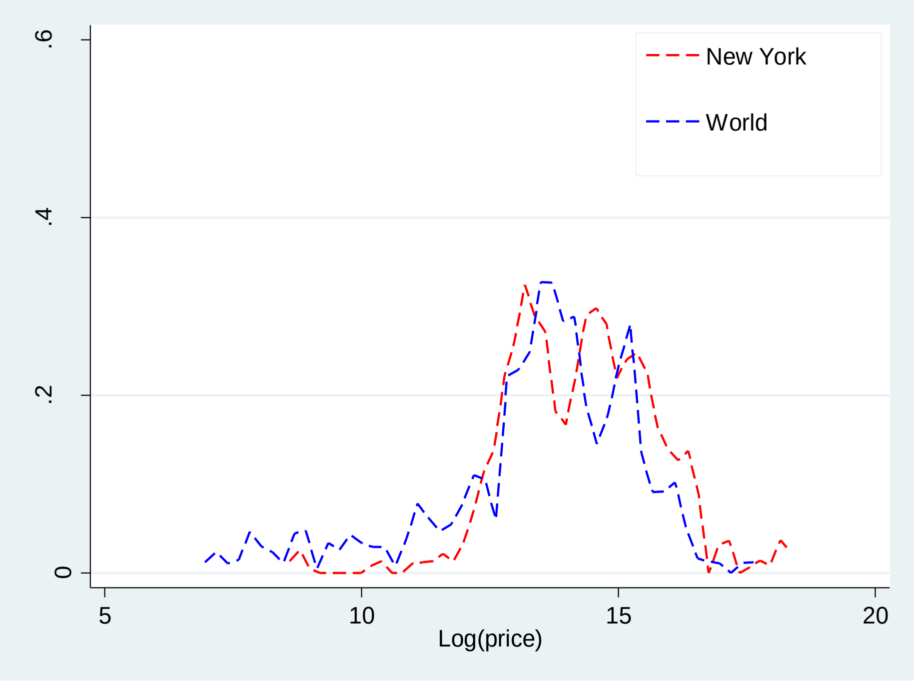
	Std Oaxaca-Blinder		RIF-based Oaxaca-Blinder							
			25th quantile		50th quantile		75th quantile		90th quantile	
	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.
overall										
difference	.647***	.111	.436***	.128	.350***	.127	.596***	.143	.538***	.149
explained	.372***	.136	.160	.145	.207	.192	.222	.187	.229	.215
unexplained	.275*	.149	.275	.178	.143	.211	.374*	.218	.309	.246
characteristics (explained)										
size	.045*	.027	.023	.015	.060*	.037	.061*	.038	.067*	.042
media	.115***	.038	.133***	.039	.098*	.041	.028	.032	.053	.039
auctions	.236*	.109	.101	.123	.131	.164	.157	.161	.048	.187
style	.043	.034	-.010	.028	.051	.044	.067*	.041	.101**	.048
time	-.067	.046	-.087*	.049	-.133**	.064	-.092*	.057	-.041	.061
coefficients (unexplained)										
size	.165***	.065	.147*	.085	.171**	-76	-.063	.091	.058	.098
media	-.353*	.193	-.397*	.245	-.042	0,25	-.662**	.279	.080	.308
auctions	.106	.351	-.165	.413	.092	.515	.193	.521	.084	.600
style	.023	.101	-.092	.131	.123	.126	-.023	.145	.050	.158
							-			
time	-.054	.436	.617	0,544	-.163	.585	1.340**	.635	-.545	.709
constant	.388	.687	.166	.833	-.038	.965	2269**	1.009	.581	1.146

Decomposition results

Kernel density



1990-1999



2000-2010

The two-sample Kolmogorov-Smirnov test rejects the null hypothesis that the logarithmic prices for the two groups (NY vs. RoW) come from the same distribution (the p value is 0.000) for both sub-samples.

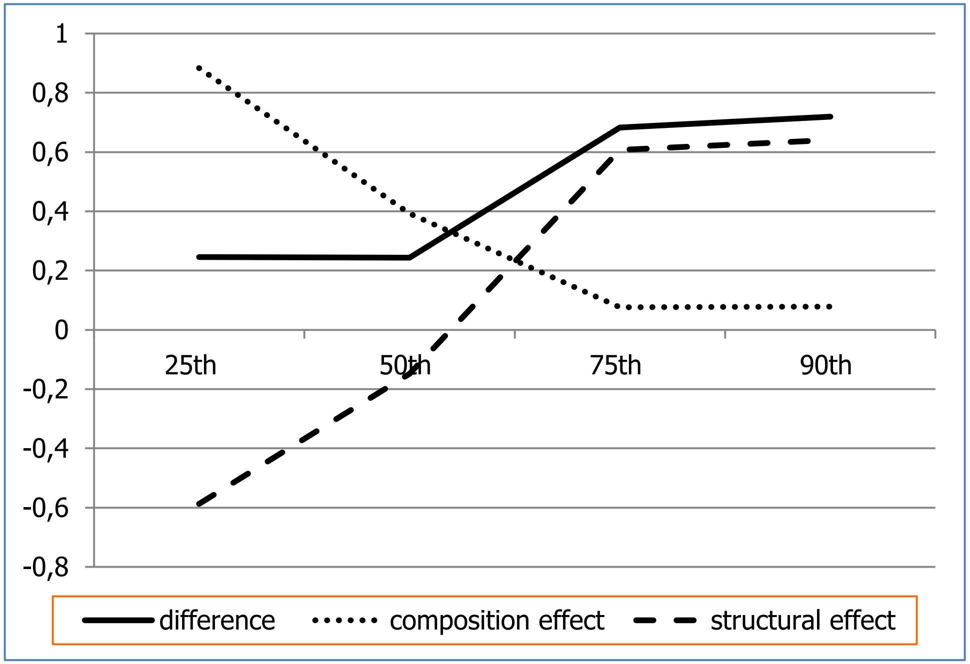
Decomposition results

Decomposition analysis: NY vs. RoW (1990-1999)

	Std. Oaxaca Blinder		RIF-based Oaxaca-Blinder							
			25th quantile		50th quantile		75th quantile		90th quantile	
	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.	Coef	Std. Err.	Δ	Std. Err.
overall										
difference	.526***	.145	.246	.155	.244	.155	.683***	.196	.719***	.240
explained	1.060***	.374	.833*	.489	.392	.485	.076	.632	.078	.796
unexplained	-.534	.366	-.587	.496	-.148	.491	.607	.639	.641	.811
characteristics(explained)										
size	.212***	.070	.163***	.057	.221***	.074	.257***	.087	.279***	.097
media	.030	.038	.097*	.051	.014	.036	-.048	.045	-.027	.051
auctions	.831*	.355	.562	.481	.177	.474	-.082	.620	-.295	.784
style	.062	.061	.042	.041	.081	.070	.145	.093	.180*	.109
time	-.075	.058	-.031	.059	-.102	.074	-.197**	.086	-.058	.104
coefficients (unexplained)										
Size	-.027	.086	.048	.124	.148	.117	-.021	.147	-.207	.189
media	.111	.229	-.066	.324	.024	.310	-.004	.392	.412	.501
auctions	1.498**	.698	.916	.961	.352	.950	-.093	1.241	-.555	1.569
style	-.051	.115	-.073	.162	.061	.155	.049	.195	-.180	.253
time	-.089	.331	.044	.468	.147	.451	-.847	.579	-.770	.740
const	-1.976	1.102	-1.456	1.531	-.879	1.508	1.525	1.965	1.940	2.488

Decomposition results

Decomposition analysis: NY vs. RoW (1990-1999)



- ❑ For higher quantiles differences in characteristics explain a large proportion of the difference between two groups (lines closed and follow the same direction)
- ❑ For lower quantiles structural effect explain more of the differences between two groups

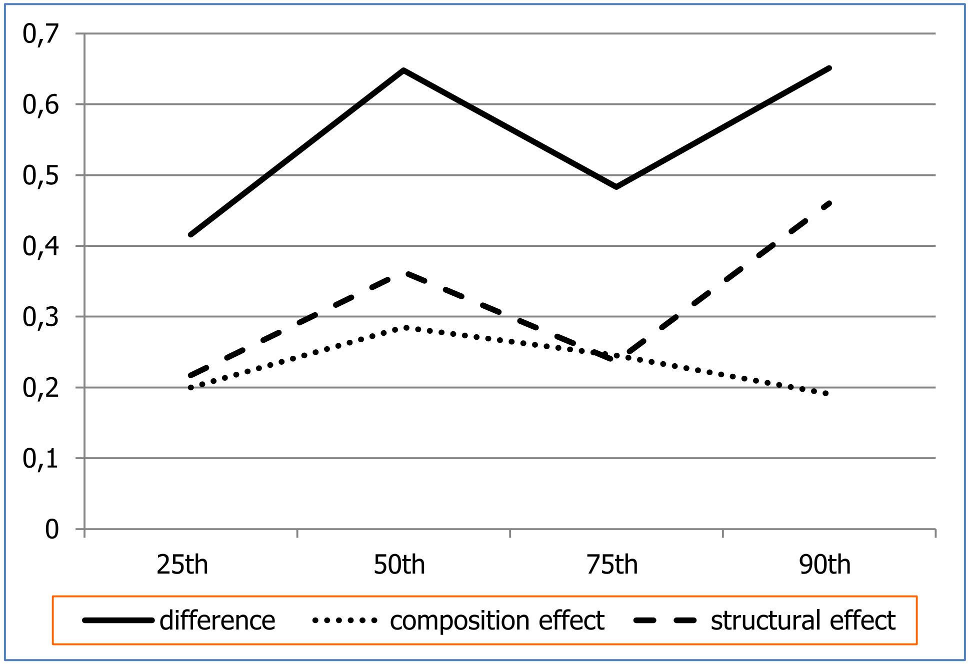
Decomposition results

Decomposition analysis: NY vs. RoW (2000-2010)

	Std. Oaxaca-Blinder		RIF-base Oaxaca-Blinder							
			25th quantile		50th quantile		75th quantile		90th quantile	
	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.
overall										
difference	.842***	.166	.416**	.207	.648***	.186	.483**	.200	.651***	.201
explained	.367***	.128	.200	.152	.285*	.172	.245	.165	.191	.185
unexplained	.475***	.171	.217	.228	.363*	.225	.237	.228	.460*	.252
characteristics (explained)										
size	.022	.030	.013	.019	.032	.044	.036	.049	.017	.025
media	.247***	.072	.225***	.077	.232***	.084	.145*	.067	.136*	.078
auctions	.117	.075	.102	.095	.037	.110	.089	.102	-.015	.122
style	.015	.042	-.053	.051	-.011	.050	.054	.061	.105	.070
time	-.034	.051	-.088	.066	-.005	.070	-.078	.072	-.053	.077
coefficients (unexplained)										
size	.257***	.099	.374***	.138	.094	.111	-.018	.130	-.057	.130
media	-.314	.268	-.638*	.364	-.053	.356	-.311	.369	.191	.405
auction	-.674	.455	-.399	.603	-.582	.655	-.261	.633	-.364	.733
style	.093	.144	.169	.198	.078	.180	.137	.198	.158	.207
time	-.196	.561	-.440	.759	-.173	.745	-.139	.773	-.093	.846
const	1.309	.869	1.151	1.166	1.000	1.203	.829	1.204	.626	1.357

Decomposition results

Decomposition analysis: NY vs. RoW (2000-2010)



- ❑ From 25° to 75th quantile both composition and structural effects explain the difference between two groups
- ❑ For higher quantile structural effect explain more of the differences between two groups

Conclusions

- This study sheds light on the factors that contribute to differences in price returns among markets
- Unconditional quantile RIF-regression show differences between covariates along the entire distribution of log price.
- Differences between NY and RoW are decomposed into a part explained by differences in the distribution of characteristics (composition effect) and a part explained by differences in the impact of these characteristics (structural effect).
  - In the 2000-2010 the structural effect is important in explaining differences between markets in the upper end of the distribution

    → *NY premium return for top paintings*

- This method can be easily applied to other non-standard investment markets.

Thank you!