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DOES THE LAW OF ONE PRICE HOLD IN NON-STANDARD INVESTMENT MARKETS? WHY SELLING PICASSO IN NEW YORK IS DIFFERENTS

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Does the law of one price hold in non-standard investment markets? Why selling Picasso in New York is different

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ABSTRACT

In the art market there is evidence that arbitrage does not necessarily equalize prices of comparable objects across different cities of sale. The aim of this study is to analyze why the distribution of prices differs between New York (NY) and the Rest of World (RoW). Two questions are addressed: (i) does the distribution change because items sold in NY have different characteristics than items sold in the RoW? (ii) is the distributional change unrelated to these characteristics, and attributable to differences in the hedonic price functions across markets? The unconditional Recentered Influence Function (RIF) regression method is used to investigate the differences across quantiles in the distribution of returns. Secondly, based on quantile RIF-regressions, we decompose price distributions across different markets. This method decomposes the price differential for any quantile. Our main finding is that arbitrage seems to happen with Picasso's 'blue chips', represented by the early (and more expensive) works, while it fails with Picasso's later paintings, which are much more heterogonous and whose value on the market is lower.

JEL Codes:

Keywords: Art market; law of one price; Picasso; RIF regression

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1. INTRODUCTION

The Law of One Price (LOP) implies that identical assets must have identical prices; otherwise, astute investors could make profits by buying assets in one market and selling them in another to profit from unjustifiable price differences. If the LOP holds, there should be no market segmentation, while persistent differences in price levels may signal that barriers remain.

In reality numerous violations of LOP have been detected, and testing its validity is particularly challenging in non-standard investment markets, typical examples of which include fine wines, antiques, boats, vintage cars and art works. In fact, arbitrage is generally easier in financial markets than in goods markets, since there are no transportation costs, and it holds not only in the long run, but almost instantaneously, since one can quickly buy and sell securities (Lamont and Thaler, 2003). Moreover, goods in different locations differ in attributes and markets are highly segmented and dominated by a few large auction houses where only a small number of assets are presented for sale throughout the year (Worthington and Higgs, 2004). Consequently, due to the partial absence of the restrictions implied by the strict definition of the LOP, i.e. identical goods, the absence of risk and the possibility of resale (Pippenger and Phillips, 2008), serious doubts arise about the validity of the LOP in the for non-standard investments and arbitrage cannot be relied upon to set their prices efficiently.

What does explain the price differences across markets after controlling for asset characteristics? In order to answer this question we have specifically chosen to study art markets because of the heterogeneous nature of the items sold, which amplifies the difficulties to apply the LOP. In the art market there is evidence that arbitrage does not necessarily equalize prices of comparable objects across countries (Pesando, 1993; Førsund and Zanola, 2006; Renneboog and Spaenjers, 2013). Of course, art markets differ from financial markets (Worhington and Higgs, 2004; Mandel, 2009), however, it is widely accepted that art is a potential investment as part of a portfolio of assets. According to the European Fine Art Foundation, despite slowing economic growth and continuing uncertainty in the global economy, the total size of the global art market was about $47.4 billion in 2013. Although the Chinese market has rapidly emerged to shake the West's dominance of the art market, in 2013 the United States was still the key center for sales, accounting for 38 per cent of the market value, while China accounts for 24 per cent and the UK was in third position, at 20 per cent (Mc Andrew, 2014).

The aim of this study is to analyze why the distribution of prices differs between New York (NY) and the Rest of World (RoW): using hedonic price indexes to control for the heterogeneous nature of non-standard investments (Ginsburgh and Throsby, 2006). Two different questions arise: (i) does the distribution change because items sold in NY have different characteristics than items sold in the RoW? (ii) is the distributional change unrelated to item characteristics, and attributable to differences in the hedonic price functions across markets? In other words, how much of this change is due to a change in the distribution of the covariates(the explained or sample composition component) and how much is due to a change in the coefficients of the hedonic price function (the unexplained or structural component)? Evidence of the latter is used as evidence against the law of one price.

To decompose such differences across the full distribution of prices, this study goes beyond simple Oaxaca-Blinder comparisons of means. This is because means are not necessarily informative about developments in the upper tail of the price distribution (Johar et al., 2013). In order to estimate unconditional partial effects, i.e. marginal effects at quantiles of the marginal distribution of prices, several approaches are available (Machado and Mata, 2005; Firpo et al., 2011; Bourguignon et al., 2004). In what follows we apply the unconditional Recentered Influence Function (RIF) regression method, based on Firpo et al. (2009), to investigate the differences across quantiles in the distribution of returns. Secondly, based on quantile RIF-regressions, we decompose price distributions across different markets. This method decomposes the price differential for any quantile in the same way means are decomposed using the standard Oaxaca-Blinder decomposition (Kassenbohmer and Sinning, 2010).

We apply this approach to an analysis of the returns from Picasso paintings, motivated by the homogeneity, quality and condition of the art items (Pesando, 1993; Czujack, 1997; Scorcu and Zanola, 2011). Our main findings show that arbitrage applies with Picasso's 'blue chips', represented by the early (and more expensive) works, while it fails with Picasso's later paintings, which are much more heterogonous and whose value on the market is lower.

2. METHODOLOGICAL FRAMEWORK

2.1. Unconditional RIF-regression

This study applies the RIF-regression method based on Firpo et al. (2009) to extend the hedonic regression approach and to investigate the differences across quantiles in the distribution of prices. This allows the relative contributions of the explained and unexplained components of the price difference to vary across the distribution of price levels from low to high value art works. The method consists in running a regression of a transformation - the Recentered Influence Function (RIF) - of the price variable on the explanatory variables. This combines both within-group and between-group effects as compared with conditional quantile regressions that are restricted to a within-group (or quantile) interpretation (Firpo et al. 2009; Fortin et al. 2011). Closely following their description of the procedure and notation, in this section we briefly outline these methods. Let *Y* be a random variable with cumulative distribution function $F_Y(y)$ and let $v(\mathrm{F_Y})$ be any functional, assumed to be linear for simplicity. The influence function (IF) of *v* at F_Y describes the influence of an infinitesimal change in the distribution of a sample on a real-valued functional distribution or statistics. Firpo et al. (2009) consider the τth quantile, q_τ as the distributional statistics $\nu(F_Y)$ and show that the IF can be expressed as:

$$IF(y, q_\tau) = \frac{\tau - I(y \leq q_\tau)}{f_Y(q_\tau)} \tag{1}$$

where f_Y is the marginal density function of Y, and I is an indicator function. The Re-centered Influence Function (RIF) for the quantile of interest q_τ is:

$$\begin{aligned} RIF(y, q_\tau) &= q_\tau + IF(y, q_\tau) \\ &= q_\tau + \frac{I(y > q_\tau)}{f_Y(q_\tau)} - \frac{1-\tau}{f_Y(q_\tau)} \\ &= a_\tau I(y > q_\tau) + b_\tau \end{aligned} \tag{2}$$

where $a_\tau = 1/f_Y(q_\tau)$ and $b_\tau = q_\tau - (1-\tau)a_\tau$. The RIF-regression model consists in regressing the RIF, given in equation (2), on the set of covariates X. The conditional expectation of the RIF is :

$$E(RIF(Y,q_\tau)|X=x) = a_\tau E[I(y>q_\tau)|X=x] + b_\tau$$
$$= a_\tau Pr[I(y>q_\tau)|X=x] + b_\tau$$

(3)

Since $E(RIF(Y,q_\tau)|X=x)$ in Equation (3) is linear in $Pr(I(y>q_\tau)|X=x)$, the average marginal effect of covariates, $\widehat{\beta}_\tau$, can be consistently estimated using OLS regression in a linear probability model (Firpo et al., 2009). In practice, in a first step the RIF is estimated by replacing q_τ and $F_y(q_\tau)$ by their observable counterparts estimated by the sample τ-*th* quantile of *Y* and a standard nonparametric density estimator (kernel), respectively. The second stage regresses the estimated RIF on *X* using a standard OLS estimator.

2.2. RIF-based decomposition

To decompose the differences in prices between NY and the RoW, we first estimate the RIF-regression for each market, m, where $m = NY\ or\ m = RoW$. The total difference in prices across quantiles between the NY and the RoW market is expressed as:

$$\underbrace{E\left(RIF\left(Y_{NY,q_\tau}|X_{NY}\right)\right) - E\left(RIF\left(Y_{RoW,q_\tau}|X_{RoW}\right)\right)}_{\Delta_{\tau,O}} = \underbrace{(\bar{X}_{NY} - \bar{X}_{RoW})\beta_{\tau.NY}}_{\Delta_{\tau,X}} + \underbrace{(\beta_{\tau.NY} - \beta_{\tau.RoW})\bar{X}_{RoW}}_{\Delta_{\tau,\beta}}$$

(4)

By replacing $\beta_{\tau.m}$ in (4) by its estimate $\widehat{\beta}_{\tau.m}$, both components can be evaluated as:

$$E(\widehat{\Delta}_{\tau,X}) = (\bar{X}_{NY} - \bar{X}_{RoW})\widehat{\beta}_{\tau.NY}$$

$$E(\widehat{\Delta}_{\tau,\beta}) = (\widehat{\beta}_{\tau.NY} - \widehat{\beta}_{\tau.RoW})\bar{X}_{RoW}$$

(5)

The first component, $\Delta_{\tau,X}$, is the explained component of the market difference, which is explained by differences in observed characteristics at the mean, weighted by coefficients attributable to NY, $\widehat{\beta}_{\tau.NY}$. The second term, $\Delta_{\tau,X}$, is the unexplained component. It is the difference in the return to observable characteristics of NY and RoW, evaluated at the mean set of the RoW's

characteristics and it can be interpreted as an estimate of market arbitrage after adjusting for differences in observable characteristics.

3. DATA

The purpose of this study is to analyze why the distribution of prices differs between New York and the Rest of World (RoW) using a RIF-based decomposition method. To test this we focus on Picasso paintings (Pesando, 1993; Czujack, 1997; Scorcu and Zanola, 2011). All data are obtained from Artnet, a large online auction sales database which contains records of paintings sold at the World's major auctions. Prices are gross of the buyers and sellers' transaction fees paid to auction houses and are expressed in US dollars, deflated using the US CPI (2000=100).

The data employed in this study consists of 907 Picasso paintings sold at auction worldwide during the period 1989-2010. The years ranging from the late 1980s to the start of the 1990s represent the great art boom. A favourable macroeconomic climate encouraged new collectors to buy works of art. During the first Gulf War, the lack of liquidity of major financial markets combined with the bankruptcy of financial institutions and the economic climate of recession affected the art market and prices shrank by 55 per cent between 1990-1993. A recovery of the art market was delayed until the late 1990s. During this period, Pablo Picasso was the investment star with paintings, like *Le rêve*, whose owners, the Ganzes, paid the sum of $7,000 for it in 1941 and sold it in 1997 at Christie's for $49million. The art market experienced a substantial crash in 2008, at the time of the worldwide financial crisis. Prices of contemporary, modern and impressionist artwork decreased about 30%. The market started to recover from late 2009. Both Sotheby's and Christie's had an increase in sales in 2010, with Christie's annual sales of $5 billion in 2010, up 53% since 2009, and with Sotheby's annual sales of $4.3 billion.

Physical characteristics included in the study are the surface area of the painting, *size;* and a set of dummy variables, reflecting the technique adopted: *canvas*, oil on canvas; *panel*, oil on panel; *mixed*, mixed media techniques; and *other_tech*, all other techniques (excluded variable). Sale characteristics refer to auction houses and markets. Sotheby's and Christie's are known to be the leading auction houses in this kind of transaction while the most important art auction markets are in New York and London. We consider therefore: *sotheby*, for Sotheby's; *christie*, for Christie's; and *other_auc* for all other locations (excluded variable). We also identify style period

characteristics (Czujack, 1997): Childhood and Youth (1881-1901), *style1*; Blue and Rose Period (1902-1906), *style2*; Analytical and Synthetic Cubism (1907-1915), *style3*; Camera and Classicism (1916-1924), *style4*; Juggler of the Form (1925-1936), *style5*; Guernica and the 'Style Picasso' (1937-1943), *style6*; Politics and Art (1944-1953), *style7*; and The Old Picasso (1954-1973), *style8* (excluded variable). Finally, a set of time dummy variables, d_t, are introduced for each year between 1989 and 2010 (1989 baseline variable). Table 1 reports descriptive statistics for the variables used in the analysis.

[TABLE 1 ABOUT HERE]

The average price for a Picasso painting in the sample is $2,732,559 and prices range from $ 1,158 ("Taureau sous l'arbre", painting on plate sold in 2005) to $84,778,190 ("Nude green leaves and bust", oil on canvas sold in 2004), with a standard deviation of $6,955,503. The Jarque-Bera test indicates that prices are not well approximated by a normal distribution. Moreover, the measure of skewness is 7.1, reflecting a long right tail of high prices. In addition, the kurtosis is 66.7 and therefore the prices have a leptokurtic (or fat-tailed) distribution.

4. RESULTS

4.1. Unconditional RIF quantile regression

The impact on hammer prices of the covariates listed above is likely to differ across paintings. Table 2 reports RIF regression estimates at the 25th, 50th, 75th, and 90th quantiles. In the estimation each observation is weighted by the sampling weight of the painting to correct for imperfections in the representativeness of the sample. The standard errors around the estimated parameter values are obtained using a bootstrap procedure with 200 replications.

[TABLE 2 ABOUT HERE]

Recall that coefficients measure the impact of a marginal change in the distribution of observable characteristics on the corresponding unconditional quantiles of the dependent variable. Wald tests are conducted to assess significant differences across quantiles. Coefficient estimates of all price regressions are mostly significant and show the expected effects. In particular, for all

quantiles, higher dimension is associated with higher returns. Analogously, panel and canvas display a positive effect on prices in line with previous studies by Czujack (1997) and Scorcu and Zanola (2011), who consider a sample of Picasso paintings as well. By contrast, comparisons across quantiles show that the differences among them are significant in the case of mixed media: lower quantiles show a negative effect on prices; yet, higher quantiles display a positive effect on prices.

The effect associated with a sale in NY is positive for all quantiles of the price distribution. This indicates that the market where the item is sold contributes to the price differential. The market effect gets larger at the top of the price distribution and it is lower at the 50th quantile. This suggests that paintings benefit from being sold in NY, with items in the top of distribution that are likely to benefit more than those in the bottom. Concerning the main auction houses their effect on price is generally positive, but statistically not significant, probably captured by the market effect. Lastly, the style period effect is generally positive with the exception of style periods 4 and 7, which are not statistically significant (except at the higher of the distribution for style period 4).

In summary, prices are driven by both physical and style characteristics at all quantiles of the price distribution. Analogously, sale characteristics too have a positive effect on prices across quantiles, with sales in NY driving higher returns at the higher quantiles of the distribution. But what might explain such a difference in price distribution between markets? One implication of these findings is that there appears to be a potential gain for sellers from choosing NY to sell their paintings. In fact, while physical and style characteristics are out of the control of the seller, the choice of market depends upon the sellers' strategy. But in order to understand whether there is a true opportunity to gain from selling in the NY market, it is necessary to distinguish between different characteristics of the items sold and differences in the hedonic price functions across the markets.

4.2. Decomposition analysis: NY vs. RoW

This sub-section analyses the decomposition of price differences between NY and the RoW across the full price distribution. The decomposition is carried out using the estimates provided by RIF regressions in order to calculate the two components according to equations (4) and (5): the composition effect (explained component), that is attributable to the differences in covariates between NY and the RoW, and the structural effect (unexplained component), which can be interpreted as the difference in prices attributed to arbitrage.

Figure 1 plots a kernel density estimate to provide an impression of the difference of (log) prices distributions between NY and RoW.

[FIGURE 1 ABOUT HERE]

Figure 1 shows two density estimators: the red line represents the distribution of prices in the NY market while the blue line represents the distribution of prices in the RoW market. Looking at these plots we get a preliminary view of the market price differences. Both distributions are skewed to the right. However, discrepancies between the two markets occur throughout the price distributions. Consequently, Figure 1 gives support to the idea of exploring the determinants of these differences across the distribution rather than exclusively at the mean.

The differences in log prices at the 25th, 50th, 75th, and 90th percentiles attributable to differences in characteristics, coefficients and residuals are depicted graphically in Figure 2.

[FIGURE 2 ABOUT HERE]

The 'structural effect line' follows the same direction as the 'total difference line'. It accounts for almost 60 per cent of the total difference in (log) prices between NY and RoW at the 25th, 75th, and 90th percentile. By contrast, 59 per cent of the total difference in (log) prices at the 50th percentile can be attributed to the explained component. Therefore, the decomposition shows the importance of the market structure to explain the price differences between NY and the RoW, so there is evidence that arbitrage does not operate in non-standard investment markets.

The results of the detailed decomposition provide more insight into the contribution of the covariates to composition and structural effects. Table 3 presents the results of the detailed decomposition. We group the covariates into five main categories: *size, media*, *auctions*, and *style*.

[TABLE 3 ABOUT HERE]

As with the difference in means, differences in *size* show a positive contribution to the composition effect at all quantiles. The composition effect of *media* varies at different quantiles. At the first quantile it accounts for approximately 52 per cent of the total composition effect, while, although statistically insignificant, it registers the lowest contribution observed at the 75th percentile, with approximately 9 per cent of the total composition effect. A possible explanation for this result may be due to the specificity of Picasso's work. Different from most other painters,

Picasso had an eclectic attitude to style and his work was characterized by radically different approaches, the most expensive of which are the early works. Therefore, it is likely that prices are more influenced by *style* than *media* at higher quantiles.

Results on the contribution of *style* to the composition effect seem to support these arguments. At the higher percentiles the contribution of *style* is statistically significant and accounts for approximately 30 per cent and 44 per cent of the composition effect respectively at 75th and 90th percentile. Finally, although the composition effect of *auctions* varies across quantiles, it is never statistically significant.

We next turn to the structural effect. Although most of the coefficients are not statistically significant, however, some interesting insights into the contributions of specific groups to the structural effect emerge, confirming the importance of focusing on both the explained and the unexplained component of price differences between markets. In particular, size contributes to the differences in prices between NY and the RoW, but only at the lower percentiles. This pattern suggests that only smaller items seem to suffer from the difficulty to equalize prices across markets and, given the correlation between dimension and prices, it is likely that arbitrage does not work with cheaper Picasso paintings. This is unsurprising, given the characteristics of Picasso's works. In contrast to the early works, which, although different, were easily identified, Picasso's later paintings were a mixture of styles, whose value on the market is lower.

Media is another group of covariates which partially contributes to the structural effect. At the 25th and the 75th percentile it is statistically significant and, differently from the composition effect, it contributes negatively to the structural effect. Again, this result might capture the lack of arbitrage with Picasso's later paintings that are more characterized by mixed materials and techniques.

4.3. Decomposition analysis: 1990-1999 vs. 2000-2010

Although the period under scrutiny is characterized by price fluctuations, Scorcu and Zanola (2011) shows that there was a rapid decrease in the returns for Picasso's work from 1990 (the boom market period) until the late 1990s, when the trend started to show signs of growth in values. Hence, in order to check the robustness of our results, we split the period into two decades: 1990-99 and 2000-10. The kernel density estimates for the 1990-99 and the 2000-10 sub-samples (Figure 3A and Figure 3B) confirm that discrepancies between the two markets occur throughout

the price distributions, giving support to the idea of exploring the determinants of these differences across both markets and periods.

[FIGURE 3A ABOUT HERE]

[FIGURE 3B ABOUT HERE]

Analogously to the previous sub-section, we disaggregate the composition and the structural effects on the basis of sets of covariates and display the results in Figure 4A and Figure 4B for the 1990-99 and the 2000-10 sub-samples respectively.

[FIGURE 4A ABOUT HERE]

[FIGURE 4B ABOUT HERE]

At the bottom of the distribution, up to the 50th percentile, the total price difference between NY and the RoW in the period 1990-1999 is largely constant due to the offsetting effects of the composition (explained) effect, which tends to decrease, compared to the structural (unexplained) effect, which tends to increase. Beyond that point the structural effect drives the total price difference line. In the case of the 2000-2010 sub-sample the configuration of the three curves implies that the shape of the total price difference line is determined mainly by the structural effect. While both the composition and the structural effect determine the total price difference up to the 75th percentile, beyond that point the difference is mainly due to the structural effect.

What are the factors driving both the composition and the structural effects? We disaggregate these two components for the 25th, 50th, 75th, and 90th percentiles on the basis of groups of covariates as in the previous sub-section. The results are presented in Table 4A and Table 4B.

[TABLE 4A ABOUT HERE]

[TABLE 4B ABOUT HERE]

In regard to the composition effect, in the 1990-99 sub-sample *size* emerges as the main factor responsible for the price differences, whose importance increases along the price distribution. The remaining factors, namely, *media*, *auctions*, and *style*, are generally not statistically significant,

with the exception of *media* at the lowest quantile and *style* at the 90th quantile. As for the 2000-10 sub-sample, there are some differences. *Size*, *auctions*, and *style* covariates are never statistically significant, while *media* covariates have a positive influence on the composition effect. This may be related to the art market crisis during the 1990s. In fact, it is likely that more expensive Picasso paintings were 'recalled' from the market in the 1990s to reappear in the 2000s, when a rising art market was able to prize quality. As a consequence, while high quality paintings were treated as 'standard' blue chips for which arbitrage worked, the LOP did not apply to the mixed styles of Picasso's later output.

Turning to the structural effect, for both sub-samples group covariates are generally not statistically significant. The only exception is size at the lower quantile for the 2000-10 sub-sample. Again, we can interpret such a result as the difficulty for arbitrage to work with the less expensive Picasso paintings.

5. DISCUSSION

The RIF decomposition methodology has been used to explain the gender wage gap (Fortin et al., 2010). More recently a number of papers have extended such analyse outside the labour economics framework: such as the case of passive and active smoking habits among adolescents (Edoka, 2012), or medication adherence in Alzheimer's disease patients (Borah and Basu, 2013), among others. However, to our knowledge, this is the first attempt to use the RIF decomposition approach to analyze investment markets and to capture the price differences attributable to the absence of arbitrage in non-standard investment markets.

The results seem to confirm such an idea: the idiosyncratic nature of the market where non-standard investment items are sold is able to capture the price differences not explained by covariates. Although we are acknowledged that some unmeasured characteristics could also explain the observed price differences, we attribute it to the absence of arbitrage. Our trust about such an interpretation of the structural effect comes from the results of the detailed decomposition of the structural effect which are consistent with the LOP. Although Picasso paintings are not identical by definition, however, the relative absence of risk and the possibility of (easy) resale makes the 'blue-chips' early paintings more similar to standard financial items for which arbitrage works. By contrast, the mixture of styles later production fails to satisfy the characteristics that make goods able to be sold at the same price in all locations.

This paper studies price differences of Picasso paintings between NY and the RoW. The main aim is to analyze whether the LOP works in non-standard investment markets, such as the case for paintings. Our results illustrate the potential of the RIF decomposition approach in capturing the absence of arbitrage between NY and the RoW. Overall, the results suggest that NY has a positive effect on the hammer price at different quantiles. After decompositing price differences a much clearer picture emerges. The total price difference is significantly determined by the (unexplained) structural effect, suggestingthe absence of arbitrage. However, the RIF decomposition shows that only Picasso's later paintings seem to suffer from the difficulty to equalize prices across markets, in contrast to the early works, for which the restrictions of the LOP seems to apply.

Clearly, as any analysis based on statistical residuals, some unmeasured characteristics could also explain the observed price differences. Nevertheless, the results raise some interesting questions regarding the strength of methodology to isolate a 'market premium' in non-standard investment transactions. While taking into account the differences in covariates between NY and the RoW, NY still registers higher prices than the RoW due to the lack of arbitrage. This suggests that investors can select markets aiming to gain higher returns from their (non-standard) investments.

From a financial prospective, being able to isolate items whose prices might be influenced by the market where they are sold can strengthen the capacity to predict the returns from non-standard investments. The results are consistent with the idea that price differences across markets are due to the absence of arbitrage; however, deeper analysis reveals the necessity to better analyse non-standard investments, which sometimes are *de facto* 'standardized', so to be easly identified by investors. This is the case for the Picasso's early production, but many other examples could occur in non-standard investment markets.

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TABLE 1. Descriptive statistics

	Full Sample (N=907)		New York (N=487)		Rest of the World (N=420)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
price	2,781,372	7,143,813	1,890,077	4,864,613	3,369,750	8,104,781
size	.603	.947	.484	.496	.737	1.269
panel	.086	.280	.101	.302	.062	.241
canvas	.708	.455	.671	.470	.743	.437
mixed	.042	.200	.071	.256	.014	.119
other_med	.160	,367	.154	.362	.174	.379
ny	.557	.497	.587	.493	.529	.500
world	443	.340	413	.368	471	.310
sotheby	.413	.493	.406	.492	.407	.492
christie	.452	.498	.428	.495	.488	.500
other_auc	.134	.341	.165	.372	.105	.307
style1	.051	.219	.060	.237	.038	.192
style2	.019	.136	.013	.114	.021	.145
style3	.053	.224	.053	.224	.052	.223
style4	.098	.298	.082	.274	.112	.316
style5	.096	.295	.106	.308	.088	.284
style6	.142	.349	.174	.380	.114	.318
style7	.134	.341	.145	.353	.126	.332
style8	.362	.481	.327	.469		
d89	.037	.190	.070	.255		
d90	.054	.226	.108	.311		
d91	.014	.119	.029	.167		
d92	.026	.160	.053	224		
d93	.041	.198	‘.082	.274		
d94	.036	.187	.073	.260		
d95	.051	.219	.101	.302		
d96	.042	.200	.084	.277		
d97	.061	.239	.121	.327		
d98	.109	.312	.218	.414		
d99	.065	.247	.130	.337		
d00	.037	.190			.081	.273
d01	.040	.195			.086	.280
d02	.042	.200			.090	.287
d03	.028	.164			.059	.237
d04	.047	.213			.102	.303
d05	.047	.213			.102	.303
d06	.050	.217			.107	.310
d07	.069	.254			.150	.357
d08	.053	.224			.114	.318
d09	..000	.000			.000	.000
d10	.050	.217			.107	.310

TABLE 2. 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 dummies	[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	

*p<.10, **p<.05, ***p<0.01

TABLE 3. Decomposition analysis: New York vs. Rest of the World

	RIF-based Oaxaca-Blinder							
	25th quantile		50th quantile		75th quantile		90th quantile	
	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.
overall								
difference	.436***	.128	.350***	.127	.596***	.143	.538***	.149
explained	.160	.145	.207	.192	.222	.187	.229	.215
unexplained	.275	.178	.143	.211	.374*	.218	.309	.246
Composition effect								
size	.023	.015	.060*	.037	.061*	.038	.067*	.042
media	.133***	.039	.098*	.041	.028	.032	.053	.039
auctions	.101	.123	.131	.164	.157	.161	.048	.187
style	-.010	.028	.051	.044	.067*	.041	.101**	.048
time dummies	[incl.]		[incl.]		[incl.]		[incl.]	
Structural effect								
size	.147*	.085	.171**	-76	-.063	.091	.058	.098
media	-.397*	.245	-.042	0,25	-.662**	.279	.080	.308
auctions	-.165	.413	.092	.515	.193	.521	.084	.600
style	-.092	.131	.123	.126	-.023	.145	.050	.158
time dummies	[incl.]		[incl.]		[incl.]		[incl.]	

*p<.10, **p<.05, ***p<0.01

TABLE 4A. Decomposition analysis: New York vs. Rest of the World (1990-1999)

	RIF-based Oaxaca-Blinder							
	25th quantile		50th quantile		75th quantile		90th quantile	
	Δ	Std. Err.	Δ	Std. Err.	Coef	Std. Err.	Δ	Std. Err.
overall								
difference	.246	.155	.244	.155	.683***	.196	.719***	.240
explained	.833*	.489	.392	.485	.076	.632	.078	.796
unexplained	-.587	.496	-.148	.491	.607	.639	.641	.811
Composition effect								
size	.163***	.057	.221***	.074	.257***	.087	.279***	.097
media	.097*	.051	.014	.036	-.048	.045	-.027	.051
auctions	.562	.481	.177	.474	-.082	.620	-.295	.784
style	.042	.041	.081	.070	.145	.093	.180*	.109
time	[incl.]		[incl.]		[incl.]		[incl.]	
Structural effect								
size	.048	.124	.148	.117	-.021	.147	-.207	.189
media	-.066	.324	.024	.310	-.004	.392	.412	.501
auctions	.916	.961	.352	.950	-.093	1.241	-.555	1.569
style	-.073	.162	.061	.155	.049	.195	-.180	.253
time	.044	.468	.147	.451	-.847	.579	-.770	.740
constant	[incl.]		[incl.]		[incl.]		[incl.]	

*p<.10, **p<.05, ***p<0.01

TABLE 4B. Decomposition analysis: New York vs. Rest of the World (2000-2010)

	RIF-base Oaxaca-Blinder							
	25th quantile		50th quantile		75th quantile		90th quantile	
	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.	Δ	Std. Err.
overall								
difference	.416**	.207	.648***	.186	.483**	.200	.651***	.201
explained	.200	.152	.285*	.172	.245	.165	.191	.185
unexplained	.217	.228	.363*	.225	.237	.228	.460*	.252
Composition effect								
size	.013	.019	.032	.044	.036	.049	.017	.025
media	.225***	.077	.232***	.084	.145*	.067	.136*	.078
auctions	.102	.095	.037	.110	.089	.102	-.015	.122
style	-.053	.051	-.011	.050	.054	.061	.105	.070
time	[incl.]		[incl.]		[incl.]		[incl.]	
Structural effect								
size	.374***	.138	.094	.111	-.018	.130	-.057	.130
media	-.638*	.364	-.053	.356	-.311	.369	.191	.405
auctions	-.399	.603	-.582	.655	-.261	.633	-.364	.733
style	.169	.198	.078	.180	.137	.198	.158	.207
time	-.440	.759	-.173	.745	-.139	.773	-.093	.846
constant	[incl.]		[incl.]		[incl.]		[incl.]	

*p<.10, **p<.05, ***p<0.01

FIGURE 1. Kernel density: NY vs. RoW

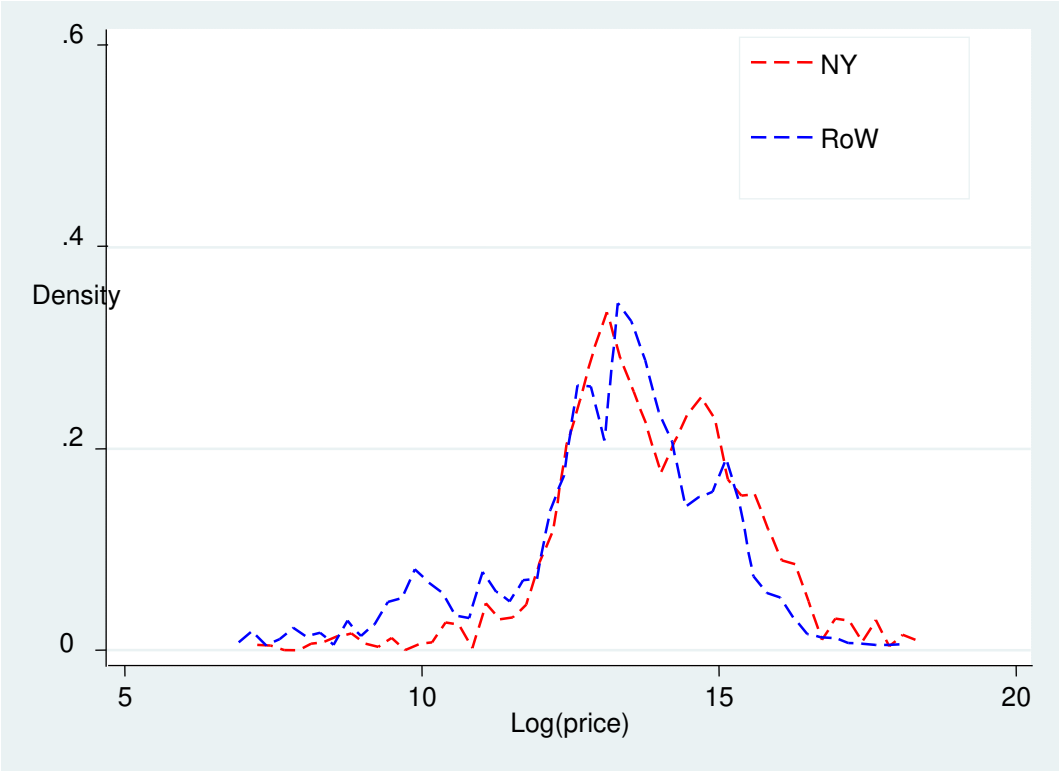


FIGURE 2. Decomposition of (log) price differences between NY vs. RoW

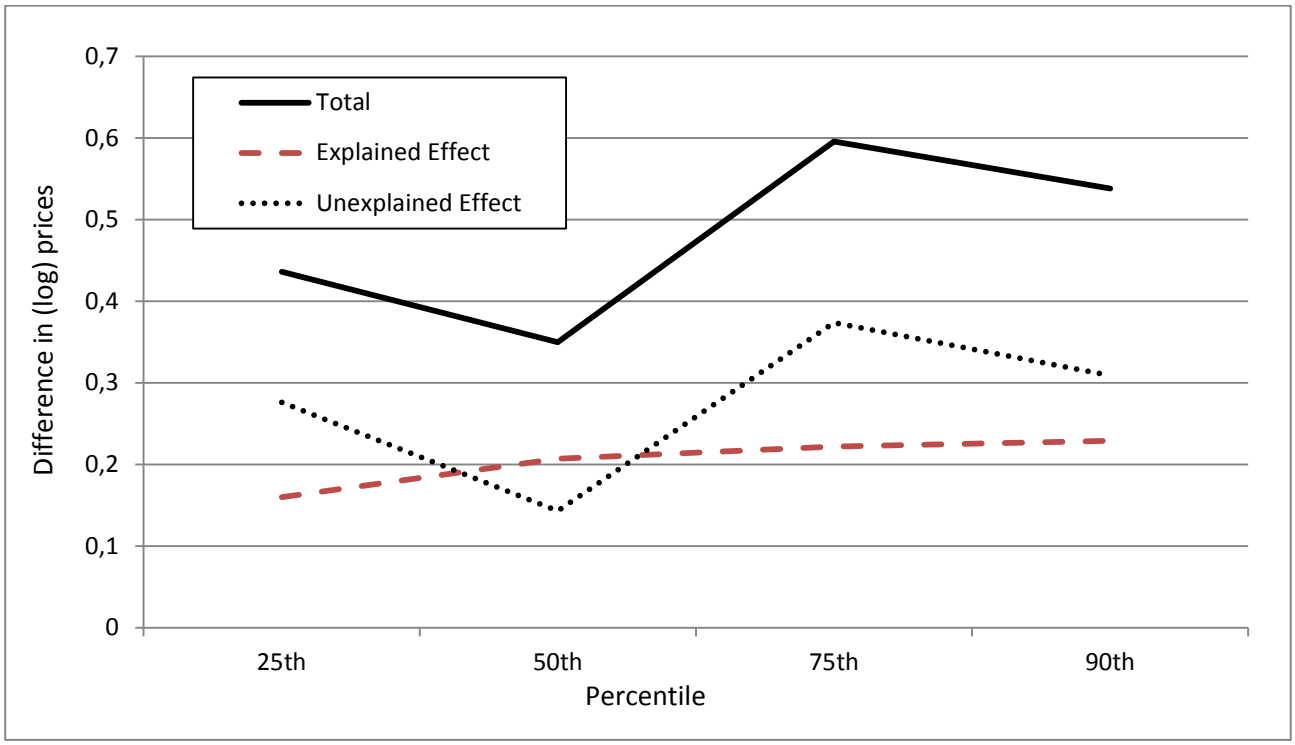


FIGURE 3A. Kernel density: New York vs. Rest of the World (1990-1999)

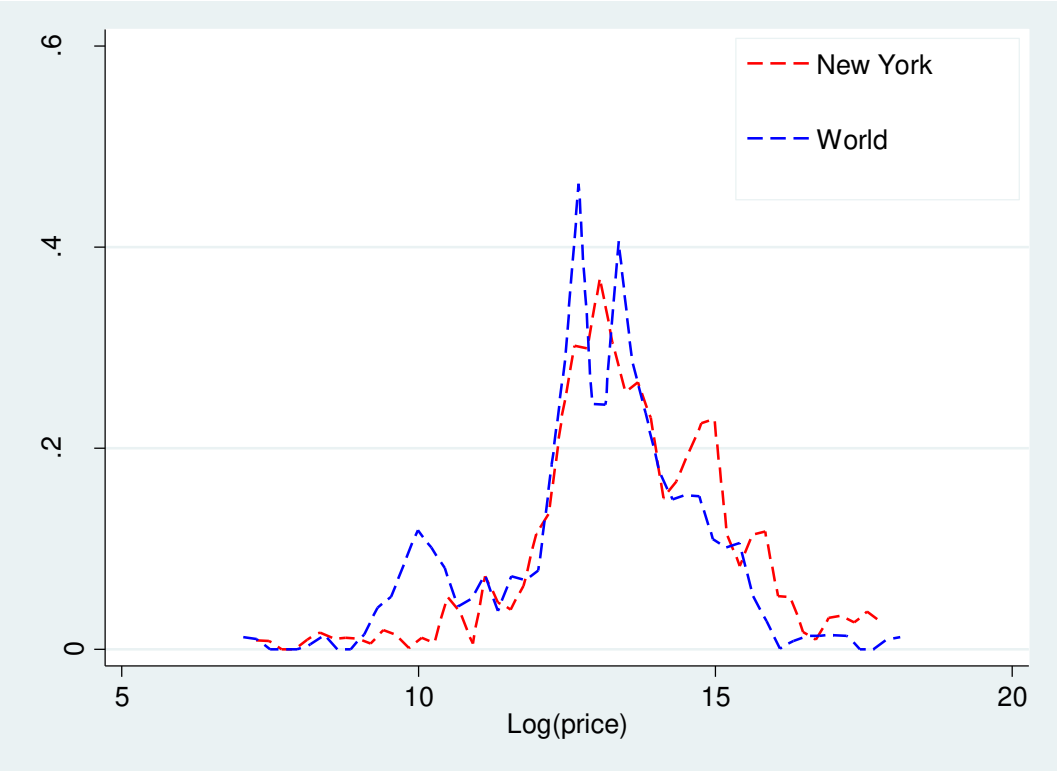


FIGURE 3B. Kernel density: New York vs. Rest of the World (2000-2010)

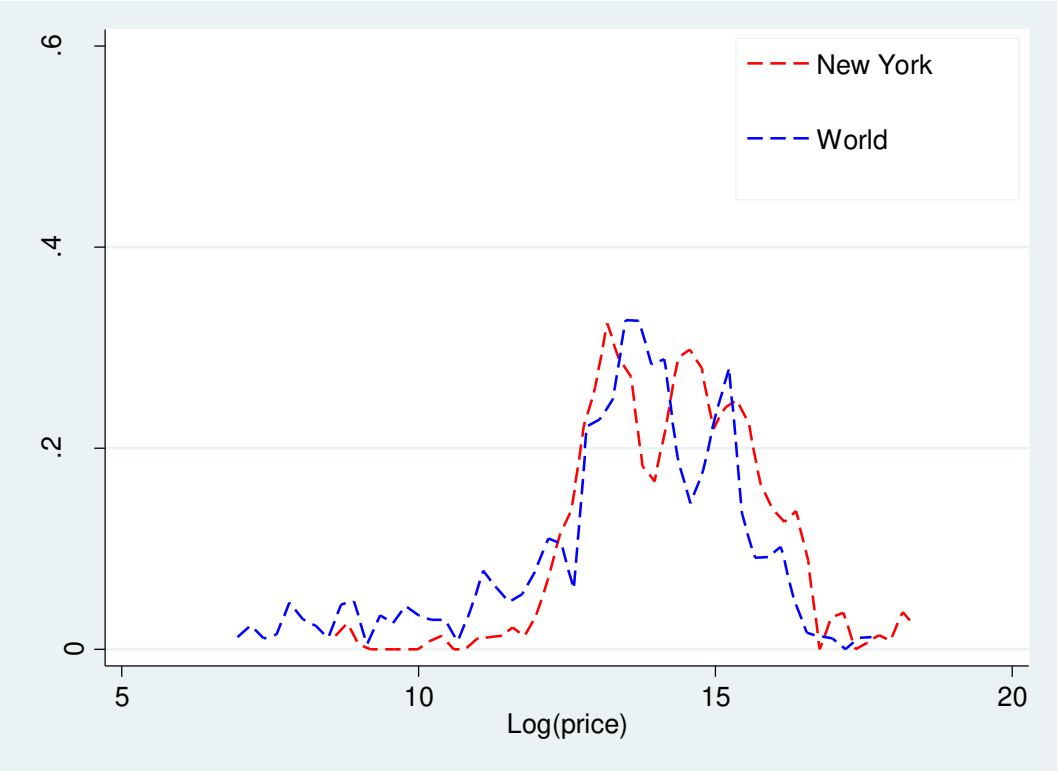


FIGURE 4A. Decomposition of (log) price differences between NY vs. RoW – 1990-1999

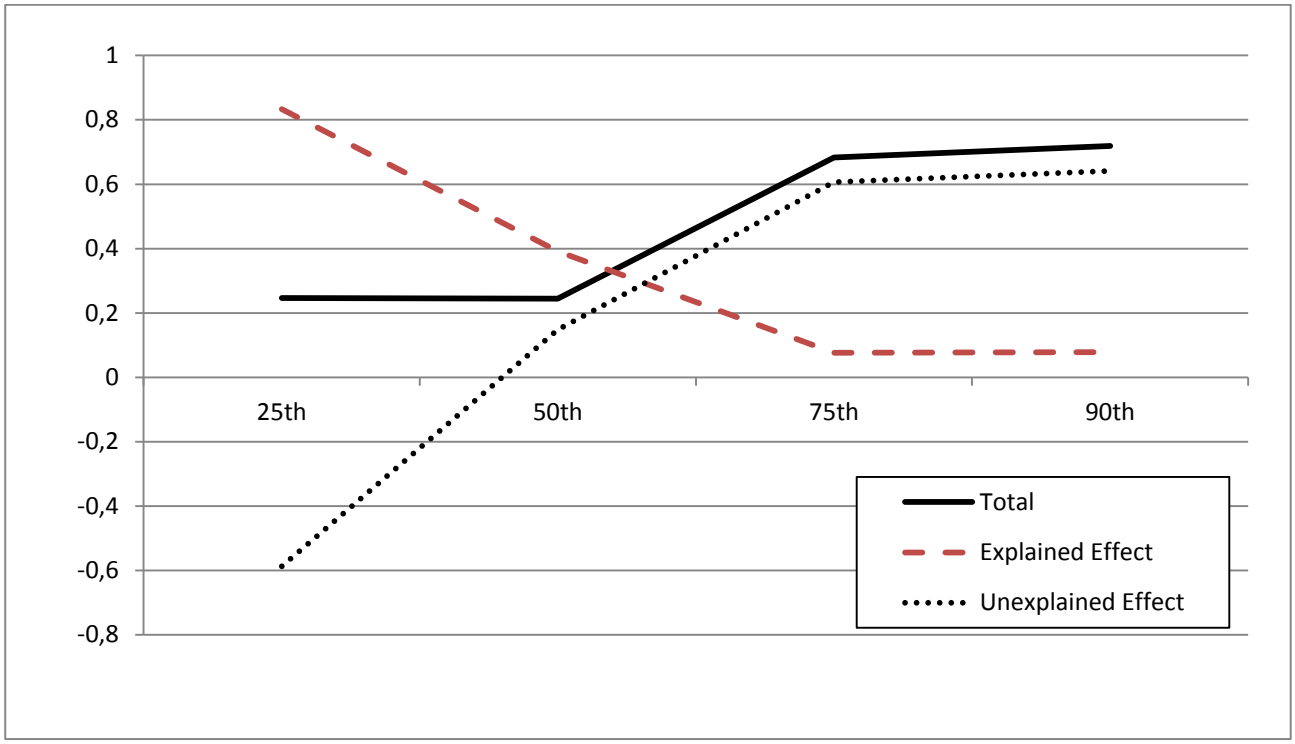
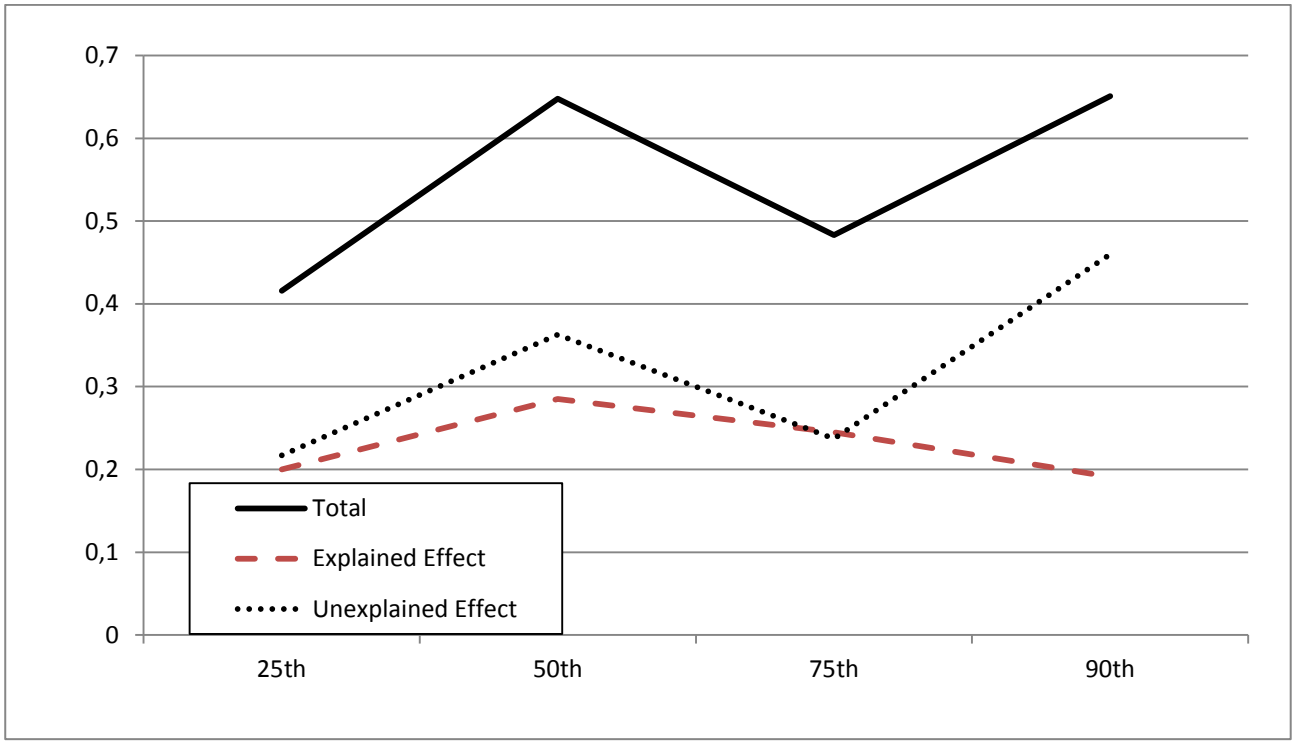


FIGURE 4B. Decomposition of (log) price differences between NY vs. RoW – 2000-2010



APPENDIX 1. Variable descriptions

Variable	**Description**
price	Price of paintings (Euros, 2000=100)
size	Area (m^2)
panel	Oil on panel
canvas	Oil on canvas
mixed	Mixed media
other_med	oOher media (omitted category)
ny	Sold in New York
world	Sold in the rest of the world (omitted category)
sotheby	Sold at Sotheby's
christie	Sold at Christie's
other_auc	Sold at other auction houses (omitted category)
style1	Childhood and Youth (1881-1901)
style2	Blue and Rose Period (1902-1906)
style3	Analytical and Synthetic Cubism (1907-1915)
style4	Camera and Classicism (1916-1924)
style5	Juggler of the Form (1925-1936)
style6	Guernica and 'Style Picasso' (1937-1943)
style7	Politics and Art (1944-1953)
style8	The Old Picasso (1954-1973) (omitted category)
d89-d10	Dummy Variables