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A Bayesian dynamic hedonic regression model for art prices

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ABSTRACT

Traditional ordinary least squares (OLS) regressions applied to hedonic pricing models assume that, when using time series, the estimated coefficients for each of the attributes remain constant. We propose a Bayesian dynamic estimation of the hedonic regression model in which the estimated coefficients can be time-varying, demonstrated with an application of art prices. Our dynamic linear regression model overcomes the problems associated with traditional rolling-window based OLS (which represent ad hoc approximations to dynamic estimation), such as under or over-estimation of parameter values and non-adaptive window sizes to account for time-variability. Using a sample of 27,124 paintings sold at auction from 63 Pop-artists (2001–2013), we demonstrate that the estimated coefficients associated with commonly used art attributes fluctuate noticeably through time, and that certain types of artworks and artists might be regarded as “safer” investments (as their art experiences smaller maximum drawdowns), based on price dynamics during the financial crisis (2008–09).

1. Introduction/motivation

The international art market has attracted a growing interest from collectors and investors from around the world. According to the annual report prepared by McAndrew (2018), $63.7 billion worth of art were traded in 2017. There is an extensive literature on the determinants of art prices built on hedonic pricing models (e.g., Campbell, 2008; Garay, 2017; Goetzmann, Renneboog, & Spaenjers, 2011; Pownall & Graddy, 2016; Renneboog & Spaenjers, 2013; Stepanova, 2015; Taylor & Coleman, 2011; Worthington & Higgs, 2005 among others).[1] Oftentimes Ordinary Least Squares (OLS) regressions have been used to estimate static versions of the model, whereby art prices are the dependent variable, and the independent variables are a set of characteristics or attributes assumed to affect art prices, such as, in the case of paintings: name of the artist, technique used (e.g., oil, acrylic, etc.), area of the painting, whether the painting is signed or dated, auction year (or semester) of the work (proxy for the economic cycle and/or overall art demand), name/perceived prestige of the auction house, etc.

In the case of art investing, one of the potential problems of applying the traditional OLS regression in the hedonic model is that it assumes that the estimated coefficients with respect to each of the attributes in the regression, when using time series, remain constant throughout the period of analysis. Even rolling window approaches, which aim at working around this limitation, still rely on locally constant (and incoherent across windows) estimates over arbitrary window sizes. This assumption of constancy in the relevance of art features on their prices is highly questionable. For example, during the recent global financial crisis of 2008–09, some market participants noted that certain types of artworks, which might be regarded as “safer” (as they have a lower maximum drawdown), experienced less abrupt declines in price when compared to others (for example, those executed in oil or acrylic versus those executed in paper). The coefficient for oil in a hedonic regression estimated through a static OLS regression would have predicted a larger price decline than what actually occurred, as it would have relied on historical bull-market performances without the flexibility to adapt to bear-markets or new environments.

In this manuscript, we propose a flexible Bayesian dynamic estimation of the hedonic model, in which these estimated coefficients relating art features and art prices can be time-varying. In the standard

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[1] The hedonic pricing model is based on the premise that the price of a marketed good (artwork, real estate, agricultural land, etc.) is related to its characteristics or attributes.

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OLS model, only the time-dummy coefficients change over time, as the shadow prices of the other variables considered in the regression (technique, signed, dated, auction house, etc.) are kept constant. Instead, in our model the coefficients for the shadow prices are allowed to vary over time, yielding the possibility of alternative interpretations and results. Section 2 presents a review on the literature on the use of the hedonic pricing model in studies of the determinants of art prices. Section 3 presents the data and the methodology used in the study, and results are outlined in Section 4. Finally, we discuss conclusions, implications, and possible extensions in Section 5.

2. Literature review

Two methods have been commonly used to estimate art returns: the repeat sales method and the hedonic pricing model. The repeat sales method analyzes, for the same painting, the prices at which a painting has been sold at auction on two or more different instances over a certain period of time. The main advantage of the repeat sales method is that it uses a standard point of comparison for all the art pieces, assuming that their characteristics remain constant over time. The main disadvantage of this method is that it can only use a very small fraction of all the paintings that have been sold at auction over a certain period of time (for example, Renneboog and Spaenjers (2013), found that only around 2% of the sales in their database of slightly more than one million lots sold were repeated sales).

Another disadvantage of the repeat sales method is that it suffers from selection bias that tends to cause an upward bias in returns (repeat sales do not occur at random across art pieces, and is oftentimes influenced by art appreciation). This arises because a painting that is presumed to have increased in price since the time that it was bought is more likely to be presented again for sale at auction, to cash in on profits on the investment, compared to the case of a painting whose price is presumed to have declined since it was bought (see Goetzmann, 1993). Using a sample of 32,928 paintings that sold repeatedly between 1960 and 2013, Korteweg, Kraeussl, and Verwijmeren (2015) estimate that removing this selection bias reduces art returns from 8.7% to 6.3% and lowers Sharpe ratios from 0.27 to 0.11. A third disadvantage of the repeat sales method is that it is often not possible to determine with complete certainty whether sales made over time correspond to the same artwork. This occurs because it is often difficult to identify whether a certain artwork sold at auction is the same that was sold in another auction without a commonly-agreed identifier. The reason for this is that, sometimes, auction houses (especially the less prestigious ones) do not provide full information regarding a lot being offered at auction (e.g., whether it is signed or dated, the technique used, and its measures). Additionally, oftentimes images are not included in auction catalogues, or are not available on art sales databases (e.g. Blouin Art and Artprice). This makes it impossible to conclude, with complete certainty, whether a painting sold at a certain auction is the same painting that was sold at another auction (at the same or at a different auction house).

The hedonic pricing model (Rosen, 1974), is estimated through a regression model in which the dependent variable is the price of each painting at each point in time. A log-transformation of prices (the dependent variable) is often used in order to mitigate the potential effects of outliers (considering that some artworks are sold for only a few thousand dollars, whereas others are sold in the tens of million dollar range). The use of log-prices for the dependent variable in hedonic regressions is almost unanimous in the literature (e.g., Agnello & Pierce, 1996; Buelens & Ginsburgh, 1993; Coleman & Taylor, 2011; Garay, 2017, 2018; Graddy & Pownall, 2016; Renneboog & Spaenjers, 2013; Stepanova, 2015; Taylor & Coleman, 2011; Worthington & Higgs, 2005).

The independent variables are the artpieces' characteristics or attributes, such as: name of the artist, area of the painting (which is usually log transformed), technique used, whether the work is signed or dated, auction year of the work, etc. The hedonic pricing method has the important advantage that it uses all available information about the sales present in a database. The main disadvantage is the inherent difficulty in selecting the variables to be used, though an argument can be made that different features could be relevant or have dynamic relevance at different periods of time. Furthermore, each attribute does not have a specific market and, therefore, its price cannot directly be observed, as highlighted in Bilbao-Terol A. Vidales-Gonzalez and Rodriguez-Alvarez (2015), who applied the hedonic pricing method to estimate the attributes of a real estate market.

Fedderke and Li (2020) conducted a hedonic regression analysis to establish the determinants of art prices in South Africa (2009–14), finding that the following attributes were significant: Identities of artists, dating characteristics, medium and genre, and physical characteristics of artwork. These authors also found that external validity of hedonic pricing was supported by out-of-sample price prediction for the case of 40 individual artists. Zhukova, Lakshina, and Leonova (2020), investigated factors that influenced the pricing of oil paintings around the world between 2005 and 2015 and determined, among other findings, that the works of Russian artists fetched higher sale prices for all sectors except for the case of contemporary art. Hedonic regressions have also been used to study the determinants of prices of other physical assets, such as real estate (Guignet & Lee, 2021), where observable and measurable asset characteristics define their values. For example, Guignet, Walsh, and Northcutt (2016) examined the impacts of ground water quality on residential property values in Lake County, Florida, finding that contamination of ground water there correspond to a 2–6 percent depreciation in home values.

Some of the studies that have applied the hedonic pricing method to estimate the influence of features or art investment returns include: Buelens and Ginsburgh (1993), Agnello and Pierce (1996), Garay (2020), Garay, Vielma, and Villalobos (2017), Graddy and Pownall (2016), Renneboog and Spaenjers (2013), Stepanova (2015), Taylor and Coleman (2011), Worthington and Higgs (2005). The work by Renneboog and Spaenjers (2013) is potentially the most comprehensive study to date in the application of the hedonic pricing model to estimate the determinants of art returns, as they studied more than one million sales of paintings at auction between 1957 and 2007. The authors found that art prices were higher when a painting: was sold at Sotheby's or Christie's (compared to other auction houses), had a larger area, was signed, was dated, was executed in oil (compared to watercolor and drawing), depended on the topic of the painting, and also depended on the month and year of the sale. The authors also found that art prices increased at a decreasing rate for larger pieces.

Tables A.1 and A.2, which have been adapted from Garay (2018), show a summary of the results found in the literature regarding the performance of art investing for studies that used the repeat sales method and those that used the hedonic pricing method, respectively. The following general inferences can be drawn:

- The real rate of return of investing in artworks has been positive in almost all cases, even though results depend on the artistic movement, and the period studied. They have also been relatively modest.
- For the majority of the studies, the recorded return of art investments is below that of stocks and, oftentimes, similar to the returns provided by government bonds, although with higher risk levels than those of bonds and with similar variability in returns experienced by stocks. This is not surprising considering that, contrary to stocks and bonds, art is both an investment and a consumption good, and hence, it provides both potential investment returns to their owners, as well as a consumption benefits. In this regard, Mandel (2009) specifies and calibrates a consumption-based capital asset pricing model (as in Lucas, 1978), and in which art is a hybrid of consumption and investment. Utility is therefore derived both from the value perceived

Table A.1
Study authors, styles (or artists, for studies with narrower foci) considered in the study, time frames of the studies, estimated annual real returns, and corresponding standard deviations (where available) from art sales extracted across different studies that used the repeated sales method (extracted from Garay (2018)).

Author(s)	Market(s)/Styles(s)	Time frame	Annual real return	Standard deviation
Baumol (1986)	General	1652–1961	0,60%	
Freand and Pommerehne (1989)	General	1635–1949	1,40%	
		1653–1987	1,50%	5,00%
		1950–1987	1,70%	
Buelens and Ginsburgh (1992)	General	1780–1970	3,00%	
Goetzmann (1993)	General	1716–1986	2,00%	5,65%
		1850–1986	3,80%	6,50%
		1900–1986	13,30%	5,19%
Pesando (1993)	Modern Prints	1977–1992	1,51%	19,94%
Chanel, Gerard-Varet and Ginsburgh (1996)	General	1855–1969	5,00%	
Goetzmann (1996)	General	1907–1977	5,00%	
Pesando and Shum (1996)	Prints by Picasso	1977–1992	2,10%	23,38%
Mei and Moses (2002)	Art from the U.S., Impressionist and Great Old Masters	1875–1999	4,90%	4,28%
		1900–1986	5,20%	3,72%
		1900–1999	5,20%	3,55%
		1950–1999	8,20%	2,13%
		1977–1991	7,80%	2,11%
Renneboog and Spaenjers (2013)	General	1982–2007	4,56%	15,79%
Korteweg, Kraussl and Verwijmeren (2015)	General	1961–2013	6,28% (Nominal Return)	11,35%

from contemporaneous art possession, and the expected price appreciation of art holdings. As a result, art returns are low since the price of artworks reflects not only the desire to smooth consumption over time (as it is the case for stocks, bonds, or any other investment alternative), but also the utility that is derived from its conspicuous consumption.

Table A.3 shows the results of the literature on the return and risk of art investments across styles/movements. All the studies listed in this table were based on the hedonic pricing model, presumably because the repeat sales method would suffer from insufficient sample sizes to extract wide conclusions.

Finally, the correlation between art returns and stocks, bonds, and most alternative investments has been found to be low (Campbell, 2008; Garay, 2017, 2020; Goetzmann et al., 2011; Kraeussl & Logher, 2010; Mei & Moses, 2002; Renneboog & Spaenjers, 2013). This common finding in the literature suggests that art offers diversification benefits to investors with standard fixed income and stock allocations.

3. Data and methodology

Paintings are usually sold at auction houses, galleries, art fairs, or through dealers. In this study, and following the literature on the determinants of art returns, we only use sale information that corresponds to auctions, because they represent the only avenue through which systematic and publicly available sources of artwork prices can be obtained.

We use data from paintings executed by artists belonging to the Pop Art movement and that were sold during the period 2001–2013. The Pop-Art movement is an artistic movement that originated in the United States and the United Kingdom in the 1950s. Its name stands for Popular Art, and it emerged as a reaction to the abstract expressionism, which had arisen in the 1940s, and which Pop artists regarded as an elitist art style. Pop-Art endeavors to be understood by everybody by conveying a simple and clear message, often using vivid colors. Pop-Art expresses and reinterprets images that are present in the popular culture (e.g., advertisement, comics, and products of mass consumption) in large cities (Osterwold, 2007). Pop-Art is regarded as one of the most important contemporary art expressions. We chose this style for our paper because we needed to work with an art movement that had a sufficient number of artists with enough sales of their paintings at auction to provide a large enough representation across the artist and time dimensions. Only a few art movements could full this requirement. For instance, we initially analyzed conceptual artists, but only a few would emerge on the database. Furthermore, conceptual works of art are more difficult to characterize (considering the nature of this artistic movement), as many of the artworks had three dimensions, thus introducing additional layers of complexity in the analysis.

Data was collected from the Blouin Art Sales database, achieving a total of 27,124 paintings executed and sold by 63 Pop-artists. The list of artists appears in Table A.4, and was selected analyzing various sources (Osterwold, 2007, www.artcyclopedia.com/history/pop.html, www.theartstory.org/movement-pop-art.htm, and the-artists.org/artistsbymovement/pop-art). These artists also had to have at least 20 artworks sold at auction during the sample period to be included in the study.[2] The artist with the highest number of works sold was Andy Warhol (8,470), followed by Roy Lichtenstein (2,432), David Hockney (1,652), Tom Wesselmann (1,463), and Keith Haring (1,220). The average number of artworks sold per artist was 430, and the average price of the paintings sold at auction by all the artists was $169,653. The most expensive painting sold in the sample was "Green car crash, green burning car I" (Andy Warhol), which sold at Christie's

[2] This is in line with the literature, where other authors, such as Edwards (2004), Garay (2017), Renneboog and Spaenjers (2013), Taylor and Coleman (2011), Worthington and Higgs (2005) have included in their studies artists having at least a minimum of between 20 to 30 paints sold at auction. As a sensitivity analysis, we ran the model considering only artists with at least 25 works sold at auction, and also at least 30 works sold at auction, and found that the results were essentially the same.

Table A.2
Study authors, styles (or artists, for studies with narrower foci) considered in the study, time frames of the studies, estimated annual real returns, and corresponding standard deviations (where available) from art sales extracted across different studies that used the hedonic pricing model (extracted from Garay (2018)).

Author(s)	Market(s)/Styles(s)	Time frame	Annual real return	Standard deviation
Agnello and Pierce (1996)	U.S.	1971–1992	9,30% (nominal US dollars)	–
Renneboog and Van Houtte (2002)	Belgium	1970–1989	8,40% (nominal belgian francs)	19,40%
Higgs and Worthington (2005)	Australia	1973–2003	6,96% (nominal australian dollars)	16,51%
Taylor and Coleman (2011)	Australian Aborigen	1982–2007	6,60% (nominal australian dollars)	17,90%
Kraeussl and Logher (2010)	Russia	1985–2008	10,00% (nominal US dollars)	26,53%
	China	1990–2008	5,70% (nominal US dollars)	21,08%
	India	2002–2008	42,20% (nominal US dollars)	36,87%
Renneboog and Spaenjers (2013)	All World	1957–2007	3,97% (real US dollars)	15,21%
Korteweg, Kraussl and Verwijmeren (2015)	General	1960–2013	8,72% (nominal US dollars)	13,76%
Renneboog and Spaenjers (2014)*	Australia	1971–2007	3,09% (real US dollars)	21,15%
	Austria	1971–2007	2,53% (real US dollars)	17,44%
	Belgium	1975–2007	−0,90% (real US dollars)	17,41%
	Canada	1972–2007	2,36% (real US dollars)	16,12%
	Denmark	1976–2007	1,75% (real US dollars)	15,56%
	France	1971–2007	1,14% (real US dollars)	18,94%
	Germany	1971–2007	1,52% (real US dollars)	13,12%
	Italy	1971–2007	1,99% (real US dollars)	17,67%
	Holland	1971–2007	2,30% (real US dollars)	17,94%
	Sweden	1971–2007	2,32% (real US dollars)	20,18%
	Switzerland	1972–2007	1,99% (real US dollars)	18,50%
	Great Britain	1971–2007	4,60% (real US dollars)	15,79%
	U.S.	1971–2007	3,07% (real US dollars)	14,31%
Edwards (2004)	Latinamerica	1981–2000	9,00% (real US dollars)	12,60%
Campos and Barbosa (2009)	Latinamerica	1995–2002	5,23% (nominal US dollars)	–
Kraussl, Lehnert and Martelin (2016)	Latinamerica	1970–2013	6,11% (nominal US dollars)	–
Garaand, Vielma and Villalobos (2017)	Argentina	1980–2014	6,81% (nominal US dollars)	29,11%
Garay (2017)*	Venezuela	1969–2014	7,96% (nominal US dollars)	33,66%

for $71.7 million in 2007. The artists with the highest average price per work sold were Thiebaud Wayne ($321,867), followed by Andy Warhol ($290,353), and Ed Rusha ($272,259). The standard deviations of the prices ranged from $1,671 to $2.15 million. Lastly, the values of skewness and kurtosis for many of the artists suggest that art prices are not normally distributed, which is expected as some works feature substantially more attention and valuation, with right-skewness and severe kurtosis anticipated for most artists.

Regarding the technique used by the artists, more than half of the artworks sold correspond to other media and prints. This is not surprising, considering that these techniques represent an essential medium of expression used by Pop-Artists. However, acrylic and oil clearly commanded the highest average prices per painting ($529,529 and $495,635, respectively), compared to other media, works on paper and prints ($137,028, $76,818, and 27,219, respectively). These results for Pop-Art are in line with those found in the literature (Renneboog & Spaenjers, 2013) although the classification of techniques varies from paper to paper. Finally, artworks sold at Christie's and Sotheby's recorded the highest average prices ($255,615 and $242,014, respectively), compared to other auction houses (averaging only $54,947). This is in line with the literature (Garay, 2018).

In line with the literature, we did not consider sculptures and any other three-dimensional works (see Vosilov, 2015, for a study of the price determinants of sculptures), as this would have required a different set of features specific to capture the 3-dimensional nature of the art pieces. Furthermore, we did not consider "buy-ins", that is, artworks that were offered at auction but were not sold because they did not reach the reserve price or minimum acceptable price set by the seller. The practice of considering only those paintings that were sold at auction has been applied extensively in the literature (e.g., Garay, 2020; Renneboog & Spaenjers, 2013; Taylor & Coleman, 2011; Worthington & Higgs, 2005). Note, however, and as was commented before, the exclusion of unsold artworks may introduce a bias. Goetzmann (1993, 1996) hypothesized that paintings that have increased in value are more likely to sell. In this regard, Goetzmann (1996) argues that survivorship could cause upward bias in the estimation of art returns. In any case, we believe that the impact of this bias on our results should be rather small, considering that, in contrast to most of the previous work, we do not require a work of art to be re(sold) only at large auction houses, as we are using a wide range of auction houses, and not only the most prestigious ones.

The hedonic pricing method assumes that the price of a painting is equal to the sum of the contributions to the prices from its attributes or characteristics.[3] Among these attributes are, for example, whether the work is signed and dated, its area, etc. (a list of attributes used in the analysis is described further below, but it contains the key features included in auctions to describe the artpieces). As we mentioned before, the hedonic pricing model has been often estimated applying the Ordinary Least Squares Method, and has the following equation:

$$\log P_{kt} = \alpha + \sum_{m=1}^{M} \beta_m X_{mkt} + \sum_{t=1}^{T} Y_t D_{kt} + \epsilon_{kt} \tag{1}$$

where

[3] Triplett (2004) offers a comprehensive review of hedonic price indexes.

Table A.3
Styles/Movements, annual returns, and standard deviations of the annual returns (where available), across different time periods, as well as styles, groupings, or geographical areas (extracted from Garay (2018)).

Style(s)/Movement(s)	Nominal annual returns (%)	Standard deviation	Nominal annual return	Standard deviation
Renneboog y Spaenjers (2012) (real dollars)	1957–2007	1957–2007	1982–2007	1982–2007
Medieval and Renaissance	3,01%	27,13%	6,44%	19,59%
Barroque	4,76%	17,69%	5,82%	12,57%
Rococo	3,69%	25,42%	5,03%	12,15%
Neoclacissism	6,32%	45,93%	5,36%	22,45%
Romanticism	4,28%	17,34%	4,79%	15,24%
Realism	2,57%	21,42%	4,16%	15,46%
Impresionism and Simbolism	4,10%	24,01%	4,55%	16,70%
Fauvism and Expresionism	3,72%	22,84%	4,90%	18,36%
Cubism, Futurism and Constructivism	5,53%	22,40%	6,01%	20,55%
Dada and Surrelism	5,85%	32,32%	5,58%	19,42%
Abstract Expresionism	–	–	7,78%	21,91%
Pop-Art	–	–	10,35%	29,33%
Minimalism and Contemporary	–	–	7,07%	23,68%
Korteweg, Kraussl and Verwijmeren (2015) (nominal dollars)	1961–2013	1961–2013		
Post-Guerra and Contemporáneo	7,43%	11,63%		
Impresionism and Modern	6,09%	13,30%		
Old Masters	4,56%	13,75%		
U.S. artists	6,83%	10,28%		
European XIX century	6,81%	11,70%		
Other styles	6,53%	13,92%		
Top 100 artists	9,50%	13,86%		
Edwards (2004) (real dollars)	1981–2000	1981–2000		
Latin America	9,00%	12,60%		
Campos and Barbosa (2009) (nominal dollars)	1995–2002			
Latin America	5,23%	–		
Kraussl, Lehnert and Martelin (2016) (nominal dollars)	1970–2013			
Latin America	6,11%	-		

- $\ln P_{kt}$: Price, expressed in natural logarithm and in nominal U.S. dollars, of painting k auctioned at time t. This price includes the "buyer's premium" or commission paid by the buyer and constitutes the dependent variable of the model.
- X_{mkt}: Value of the attribute or characteristic m of artwork k auctioned at time t.
- D_{kt}: Dummy variable that takes the value of 1 if artwork k is sold at time t and 0 otherwise.
- β_m: Contribution to the log-price of the asset per unit of the attribute m.
- Y_t: Time-specific contribution to the log-price of the asset for artwork k at time t.

Eq. (1) is based on the hedonic pricing model proposed by Rosen (1974), and assumes that the market valuation of each attribute or characteristic does not change through time. Eq. (1) has been estimated in the literature by a number of authors running an Ordinary Least Squares regression (e.g., Campbell, 2008; Campos & Barbosa, 2008; Edwards, 2004; Garay et al., 2017; Kraeussl & Logher, 2010; Pownall & Graddy, 2016; Renneboog & Spaenjers, 2013; Stepanova, 2015; Taylor & Coleman, 2011; Worthington & Higgs, 2005). The OLS contains fixed effects with respect to both time and cross-sections. It should be noted that individual effects are not present because the kth painting auctioned at time t is not necessarily the same as the kth painting sold at time t', where $t' \neq t$.

In order to accommodate the static OLS to the dynamic nature of the feature relevance on the artpiece price, authors oftentimes estimate the model over rolling windows. This approach, however, presents numerous challenges: (1) It relies on knowledge of the optimal window size a priori, which is not possible, oftentimes resulting in data snooping and overfitting; (2) It relies on the stationarity of that optimal window size (e.g., during bull or bear markets), which assumes constant speed of dynamics in the art markets (again, an assumption difficult to justify on theoretical or empirical grounds); (3) It is theoretically inconsistent (two overlapping rolling windows would assume constant, yet different, parameters, which is impossible); and (4) It is not flexible enough to allow for forecasting, with the latest window being a mere representation of the local estimates, but with a loss of the information contained in the remainder of the sample about the dynamics of the feature contributions. While rolling windows became practical approaches to allow for practical estimation of some dynamics in associations between variables, they are outdated and flawed, with better approaches available in the statistical literature to capture equivalent features in the data.

The list of the attributes considered in the regression model is presented below[4]:

- Artist name: Dummy variable equal to 1 if the painting was executed by the respective artist.
- Technique used: Paintings are categorized as having been executed using any of the following techniques (dummy variables): Oil, acrylic, works on paper, prints, and other media.
- Auction house: An indicator for auction at Christie's, Sotheby's or other auction houses.
- Dated: Dummy variable equal to 1 if the painting is dated.
- Signed: Dummy variable equal to 1 if the painting is signed.

[4] These attributes were used in their analyses by, among other authors: Renneboog and Spaenjers (2013), Taylor and Coleman (2011), Worthington and Higgs (2005) except for the variable "alive", which was used in Garay, 2017, 2020).

Table A.4
Pop-Artists (for artists with at least 20 paintings sold over the study period), listed in alphabetical order, and acronyms used in databases for those authors are listed in the first two columns. The remainder of the table includes descriptive statistics of the artists and their work for the data used in this study. All price measurements are in US dollars, and the number of works sold refers to the duration of the study period.

Artist	Acronym	Born	Died	Number of works sold	Arithmetic mean price ($)	Standard Deviation ($)	Kurtosis	Skewness
Adami Valerio	VAAD	1935	2005	446	25446.48879	34809.46799	23.1978789	3.900696081
Arman	ARMA	1928	2005	729	21196.2716	36665.99866	65.29285627	6.138224529
Artschwager Richard	RIAR	1923	2013	94	129729.4255	250719.9826	7.549742396	2.814325227
Barker Clive	CLBA	1940		24	7744.875	11009.33132	4.457329068	1.983434309
Blake Peter	PEBL	1932		108	29672.44444	73403.98902	32.4193288	5.394631649
Boshier Derek	DEBO	1937		33	3070.212121	5031.865346	4.158699735	2.283670457
Britto Romero	BRRO	1963		27	9826.740741	15444.72638	17.93792105	3.970465588
Caulfield Patrick	PACA	1936	2005	82	117493.2073	210647.3621	2.893169256	1.995390187
Chamberlain John	JOCH	1927	2011	38	16821.28947	22938.25557	3.485186649	2.035309541
Dine Jim	JIDI	1935		631	26558.78922	51469.07337	17.19543739	3.884230369
Arcangelo Allan	ALLA	1930	1998	48	91815.35417	178735.9182	9.818999293	3.125374934
Eggleston William	WIEG	1939		332	53357.72892	91424.13007	42.74455101	5.273872129
Erro	ERRO	1932		549	16704.03461	66552.88843	225.5549619	13.82615435
Fahlstrom Oyvind	OYFA	1928	1976	56	17909.26786	50889.19036	30.87610653	5.251151706
Goode Joe	JOGO	1937		20	15866.95	37916.94325	18.88359109	4.297855638
Grooms Red	REGR	1937		62	6288.080645	11360.52848	30.38501422	5.088051111
Hains Raymond	RAHA	1926	2005	174	28397.08046	39719.72847	41.00685846	5.376005536
Hamilton Richard	RIHA	1922	2011	258	26685.25194	67955.60921	71.58170329	7.865872217
Haring Keith	KEHA	1958	1990	1220	56852.39754	160918.4946	89.54884514	8.029242096
Hockney David	DAHO	1937		1652	66653.8753	390811.8418	187.0133363	12.59204269
Hopper Dennis	DEHO	1936	2010	26	25423.15385	57884.6634	23.32159829	4.727371231
Indiana Robert	ROIN	1928		306	113189.8431	273410.7835	41.35823548	5.501387268
Johns Jasper	JAJO	1930		931	187460.5252	1303472.338	284.5638318	15.16396475
Johnson Ray	RAJO	1927	1995	66	9707.212121	7668.590643	0.480004898	1.109444847
Jones Allen	ALJO	1937		101	34052.29703	93841.61684	54.97005633	6.897052702
Katz Alex	ALKA	1927		374	59089.92513	97107.15391	9.572064698	2.838629317
Kienholz Edward	EDKI	1927	1994	40	8451	11986.84324	9.933208131	3.060662403
Kitaj R B	RKIT	1932	2007	60	71947	99353.52931	7.228000015	2.647403679
Klapheck Konrad	KOKL	1935		50	80742.62	102664.6066	6.165688637	2.318033743
Kogelnik Kiki	KIKO	1935	1997	30	14169.2	18673.2697	2.616742574	1.958023326
Krushenick Nicholas	NIKR	1929	1999	27	25455.48148	38765.06938	2.605411848	1.942983403
Kusama Yayoi	YAKU	1929		533	112951.9343	257884.7145	54.35588961	6.049776069
Laing Gerald	GELA	1936	2011	26	50614.65385	116464.1294	22.65608917	4.634085773
Lichtenstein Roy	ROLI	1923	1997	2432	260896.34	2151733.254	397.1408922	18.47840349
Lindner Richard	RILI	1901	1978	73	90784.46575	182502.6667	11.27275639	3.23028067
Max Peter	PEMA	1937		130	2704.076923	2544.73816	2.562900354	1.698205991
Murakami Takashi	TAMU	1962		266	198709.3459	402364.886	41.05364988	5.179904902
Nara Yoshitomo	YONA	1959		432	107154.4676	212822.7599	16.93288121	3.818048541
Oldenburg Claes	CLOL	1929		167	27670.21557	51423.25866	26.88761668	4.691275555
Opie Julian	JUOP	1958		141	29366.57447	28312.31059	1.51559056	1.426029036
Paolozzi Eduardo	EDPA	1924	2005	80	8603.625	18116.03034	22.81476626	4.390046725
Phillips Peter	PEPH	1939		38	5621.552632	5827.809281	2.917691267	1.748857627
Polke Sigmar	SIPO	1941	2010	567	201936.1323	708400.0483	78.89858763	8.000593431
Psaier Pietro	PIPS	1939	2004	469	2532.027719	3398.867467	14.53399204	3.299772296
Ramos Mel	MERA	1935		109	137979.7064	244800.6918	15.55092948	3.430917187
Rauschenberg Robert	RORA	1925	2008	663	172295.7406	860091.9117	157.7723834	11.53669391
Rivers Larry	LARI	1923	2002	194	52018.47423	114954.7056	43.18490017	5.4996267
Rizzi James	JARI	1950	2011	25	1665.12	1670.932931	7.493116662	2.682090311
Rosenquist James	JARO	1933		262	88407.34733	177588.1703	19.21900026	3.650912863
Ruscha Ed	EDRU	1937		656	272258.9162	643201.8605	34.91679555	5.211955501
Saint Phalle Niki de	NIDE	1930	2002	196	17599.2449	59485.95021	137.4720713	10.97885061
Saul Peter	PESA	1934		58	51089.24138	59746.04093	11.35826358	3.010295831
Scharf Kenny	KESC	1958		172	24023.90116	25996.72422	8.142308143	2.460430121
Segal George	GESE	1924	2000	36	10662.33333	37966.20364	34.51278609	5.827812274
Self Colin	COSE	1941		27	2662.37037	2267.20852	1.580247494	1.484779751
Smith Richard	RISM	1931	2016	47	5817.510638	10845.19842	9.379953973	3.174885385
Takano Aya	AYTA	1976		73	65699.24658	88236.69027	6.467172437	2.475049497
Thiebaud Wayne	WATH	1920		421	321867.4537	691748.7912	11.39243071	3.216804528
Tilson Joe	JOTI	1928		105	9629.238095	24858.59272	58.30505463	6.987927941
Valdes Manolo	MAVA	1942		109	194545.422	157469.9408	−0.361803698	0.541331947
Warhol Andy	ANWA	1928	1987	8470	290352.9808	1914112.537	513.640708	19.32865416
Wesley John	JOWE	1928		90	93039.07778	104672.8333	4.609595156	1.962300373
Wesselmann Tom	TOWE	1931	2004	1463	103657.1798	396678.0175	101.8857568	8.853605076

- Area: it considers the artworks' size in square inches.
- Area squared: this variable is used to analyze whether the prices of paintings increase at a decreasing rate as the size of artworks increases.
- Year and Semester of the auction: we considered the year and the semester in which the auction was held.
- Alive: Dummy variable that takes the value of 1 if the artist was alive at the time an auction was held, and 0 if he or she had already deceased.

The full presentation and estimation procedure of our Dynamic Linear Model (DLM) appears in Appendix.

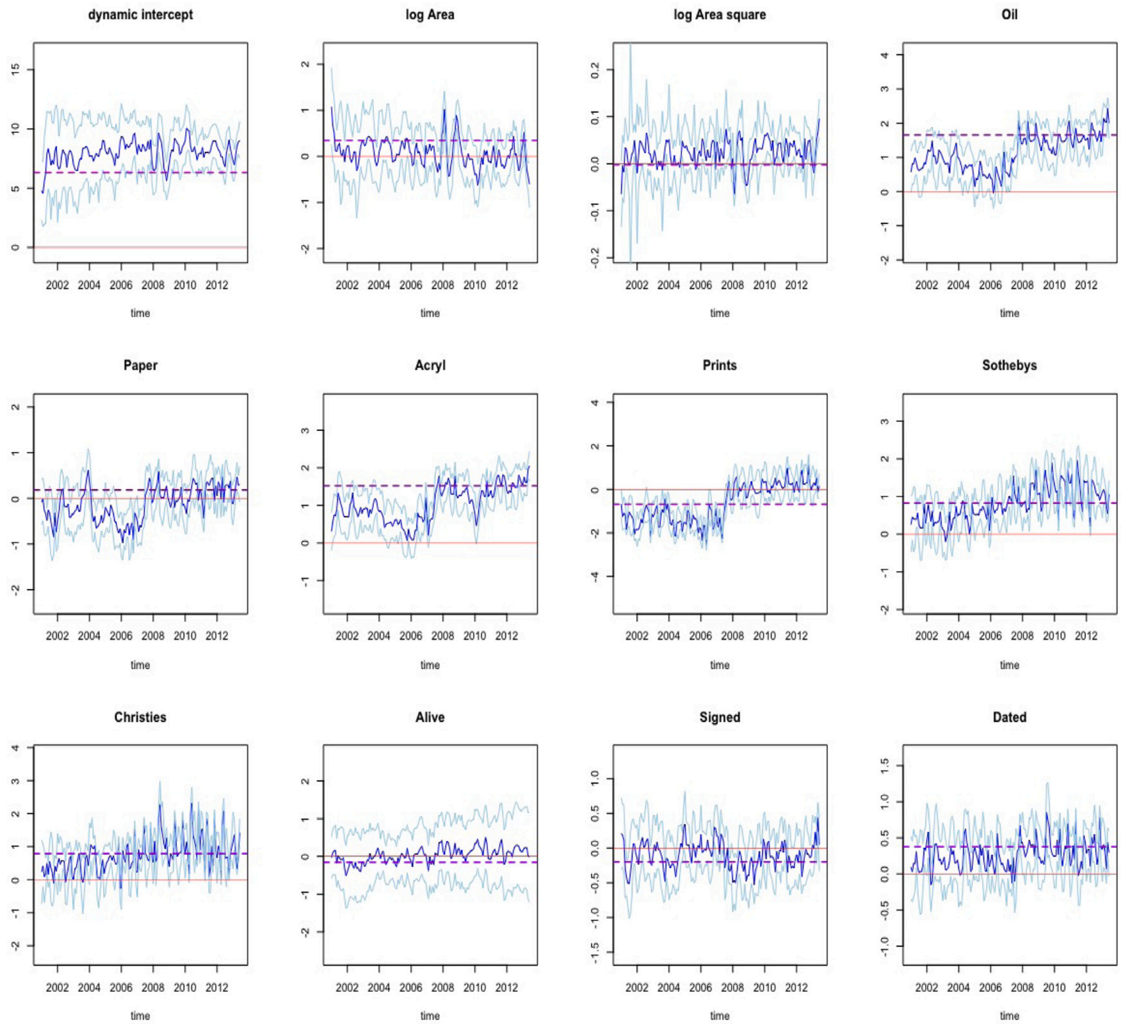

Fig. A.1. Posterior means (dark blue line) and 95% credible intervals (light blue lines) for the dynamic intercept and the dynamic coefficients for each of the art features (blue lines) and OLS estimates (dotted line), across features during the study period (2001–2013). Zero is provided as a reference with a solid red line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Blouin Art Database. Further description of the construction of each variable is provided in the body of the manuscript.

4. Results

Fig. A.1 presents the Bayesian dynamic coefficients and the dynamic intercept for the dynamic linear regression estimated using the Bayesian approach (continuous line) compared to the coefficients estimated through the traditional static OLS regression (dotted line), which can be regarded as a benchmark and baseline in the analysis. The figures reflect not only the dynamic nature of the associations but also their shifting relevance over time. Furthermore, it is noticeable that the betas of a number of the variables experienced a change in the trajectory towards the end of 2008/beginning of 2009, at the time the global financial crisis erupted, as well as an increase in volatility (between September of 2008 and February of 2009 the Standard and Poor's 500 suffered a cumulated loss of close to 60%). It could be argued that in times of crisis, the most "valuable" attributes become more important to define the artpiece's value, as suggested by an increase in the beta of the respective attribute or variable. For instance, as a result of the financial crisis, one can observe the following:

- While the betas for Sotheby's and Christie's (the most reputable auction houses) increased during the crisis (although only slightly), the estimated coefficients for the other auction houses remained constant.
- The betas for oil and acrylic (as seen in Table A.4, paintings executed using these materials tend to be more expensive) clearly increased during the crisis. Other media (relatively cheaper paintings) decreased. Perhaps surprisingly, the betas for works on paper and prints also increase around the crisis, indicating that other factors became more relevant to explain the price dynamics during this period. While these techniques are usually associated with very low prices (compared to oil and acrylic), in the case of Pop-Art, works on paper and prints are relatively expensive (compared to works on paper and prints used by artists belonging to other styles). This is very likely because they are essential to the message that Pop-Artists desire to convey.
- The betas for dated works (a sign of authenticity) increase slightly during the crisis, reflecting the increased relevance of artpieces with full information, which may be a proxy for perceived authenticity and marketability as an investment.
- The log of the area (and log of area squared) experienced sharp rises in fluctuation around the crisis, but no clear new trend afterwards.
- For a number of artists, there is also a change in the trajectory of their betas after the crisis, although for a number of them the coefficients remained relatively constant during the period of study. In general, for the most expensive artists (e.g. Andy

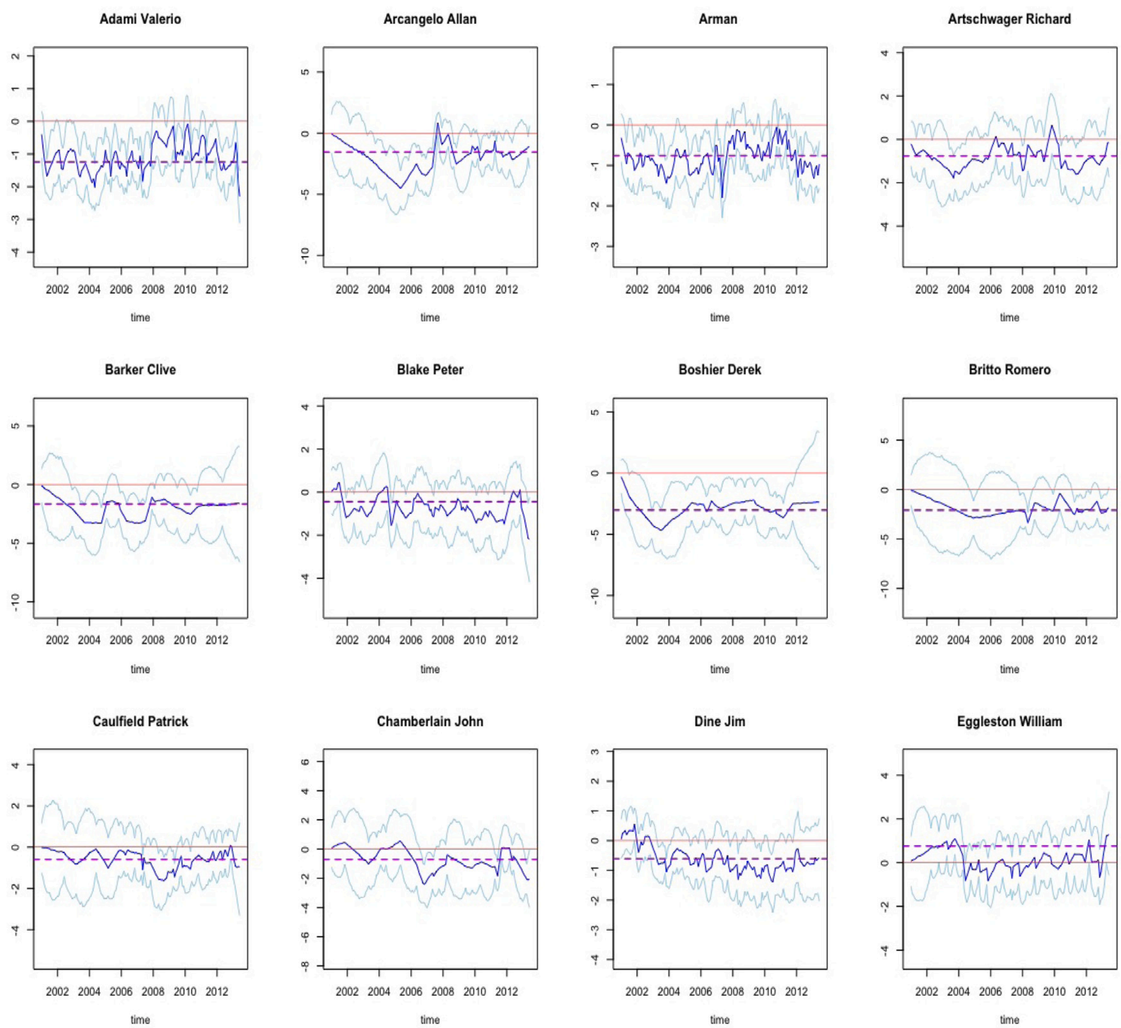

Fig. A.2. Posterior means (dark blue line) and 95% credible intervals (light blue lines) for the dynamic intercept and the dynamic coefficients for the artist-specific coefficients (blue lines) and OLS estimates (dotted line), across artists during the study period (2001–2013). Zero is provided as a reference with a solid red line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Blouin Art Database. Further description of the construction of each variable is provided in the body of the manuscript.

Warhol, Jasper Johns, Robert Indiana, Yayoi Kusama, and Nara Yoshimoto), betas increase or stop decreasing around the time of the crisis, suggesting that their works can be categorized as safer assets (at least compared to less famous artists), as reflected in Figs. A.2–A.7, which represents the dynamics by artist (time-varying artist-specific parameters). This finding is consistent with the views expressed by market participants. For example, according to George Herman, the Head of South African Portfolios at Citadel Wealth Management, buyers of art take a long-time to trust the work of an artist and therefore the most popular artists sell at a premium. He argues that *"this effect became especially apparent following the market turmoil of 2008. It is obvious that buyers consider the works of the better known artists as 'safer', hence the premium"* (www.iol.co.za/personal-finance/how-is-sa-art-market-doing-1943369, news from November 11th, 2015).

In the case of signed works, the betas decreased around the time of the crisis. This result is counterintuitive, as a signed work should command a higher level of authenticity, though it is possible that other variables captured this component. Although this variable has been found to be significant in part of the literature, for example Renneboog and Spaenjers (2013). The signed variable has been found to be non-significant in most of the literature (Garay, 2017; Graddy & Pownall, 2016; Stepanova, 2015), in part because it is not always possible to establish whether an artwork has been signed by observing the information provided by existing art price databases, highlighting this as a data quality issue more than a representation of the true nature of the association. For example, on certain occasions, a painting is signed but the respective auction house does not indicate this accurately in the auction catalogue (we have confirmed that this occurs for the case of a number of less prestigious auction houses). Perhaps, the signature is on the back of the painting, but the auction house does not provide any indication regarding this feature. In those instances, we had to assume that the work was not signed.

Finally, we also constructed a semiannual Pop-Art price index (see Fig. A.8). The index is defined as the ratio between the estimated log prices at time t and the log prices at time 0 and multiplying the ratio times 100. In the case of the static hedonic model (OLS) this is straightforward because it involves only the time (semiannual) dummy variables. In the case of the DLM, we first calculate the estimated log prices by plugging in the posterior mean for the state variables θ_t and then the ratios with respect to P_0. In Fig. A.8 we also report the mean index and the median index obtained using the descriptive mean and median of the prices at time t.

Renneboog and Spaenjers (2013) explain how, in the context of the hedonic regression model, the coefficient Y_t (regression coefficient with respect to the year-semester dummy variable), can be used to

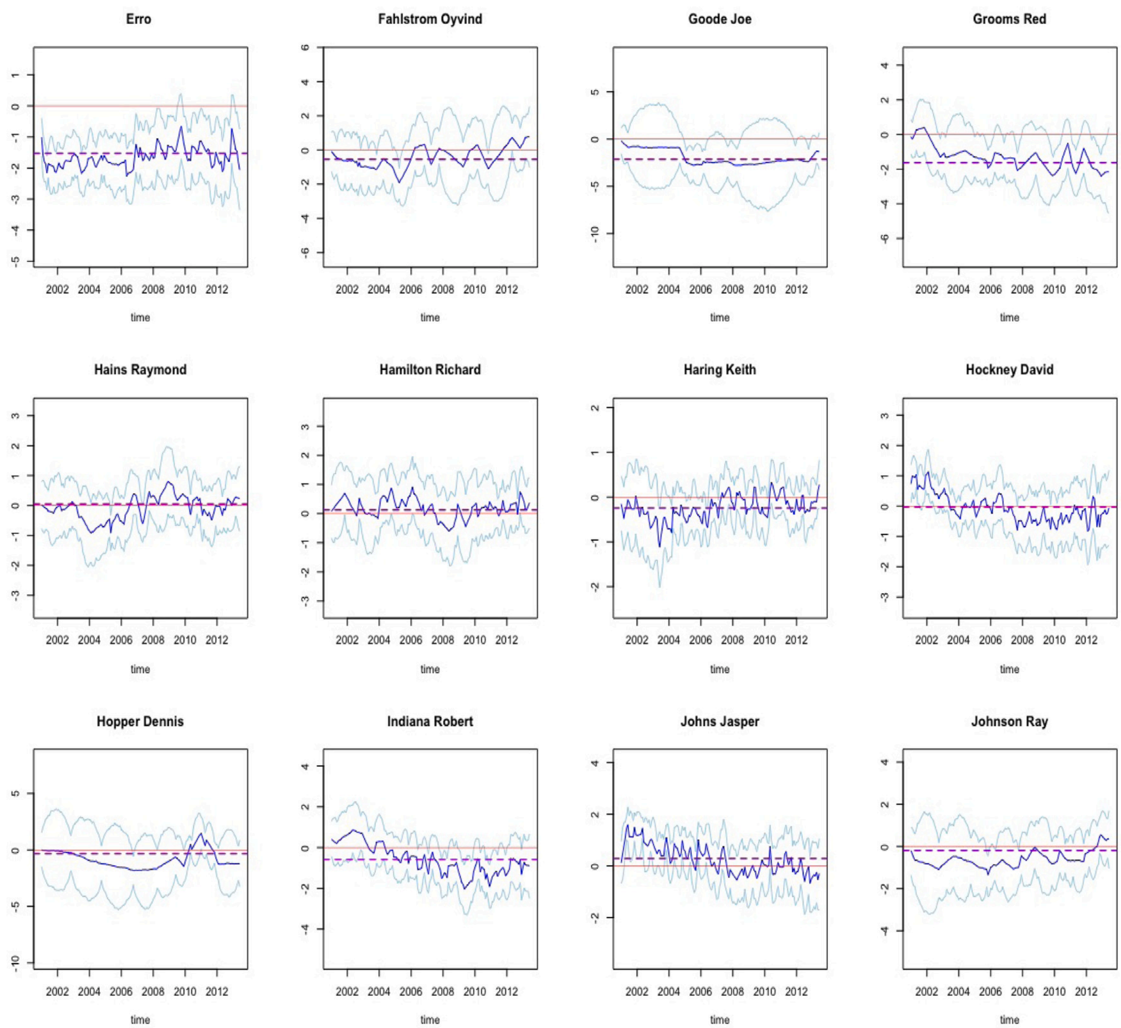

Fig. A.3. Posterior means (dark blue line) and 95% credible intervals (light blue lines) for the dynamic intercept and the dynamic coefficients for the artist-specific coefficients (blue lines) and OLS estimates (dotted line), across artists during the study period (2001–2013). Zero is provided as a reference with a solid red line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Blouin Art Database. Further description of the construction of each variable is provided in the body of the manuscript.

create a price index as $\exp(Y_t)$. The dynamic model suggests that Pop-Art prices peaked in the first semester of 2008, just before the financial crisis erupted, in line with most asset prices with positive betas to the economic cycle. For comparison, we also calculated indices using mean and median art prices, and both suggest that prices peaked in the first semester of 2007. An art price index built using a static OLS estimation indicates that, similar to the case of our estimation, that prices peaked in the first semester of 2008. Our Bayesian dynamic estimation suggests that prices increased sharply in the semesters prior to the financial crisis of late 2008 (much more so than an OLS estimation would indicate), and then plummeted in the second half of 2008 and the first semester of 2009 at faster speeds. After the crisis, the dynamic estimates remained above the OLS model, suggesting that the latter was potentially unable to capture the sharp shifts in dynamics.

5. Conclusions

We propose a Bayesian dynamic estimation of the hedonic model in which the estimated coefficients can be time-varying. Using a sample of 27,124 paintings sold at auction by 63 Pop artists between 2001 and 2013, we find that the estimated coefficients from the dynamic regression model exhibited ample fluctuations through time, and also that paintings having characteristics regarded as “safer” (as they have a lower maximum drawdown), experienced lesser declines in price when compared to less safe paintings during the 2008 financial crisis. We also estimated a Pop-Art price index that suggests that, in the semesters prior to the crisis, Pop-Art prices increased much faster than what a traditional OLS estimation would suggest, and then declined in the midst of the global financial crisis (2008–2009) at faster speeds.

The results demonstrate that the assumption of constant coefficients is not empirically grounded, and novel approaches are needed to capture not only differences in the relevance of features on prices over time, but also differentials in the speed in which these associations evolve. While some features appeared to be non-relevant during the study period, this is expected, as the relevance of features defining the buyer’s preferences regarding artworks evolves over time and with societal changes. Additionally, by using a Bayesian approach, our results produce a parametric representation where outcomes are representations of the information content of the data about the quantities of interest, instead of estimators reliant on asymptotics.

Our approach could also be applied to hedonic studies in other asset classes, such as real estate, where the characteristics or attributes of this asset class can also be expected to behave dynamically through time and relate to a set of measurable characteristics that uniquely define the asset.

The proposed approach allows for future research such as extraction of time-series clustering analysis (Nieto-Barajas & Contreras-Cristan,

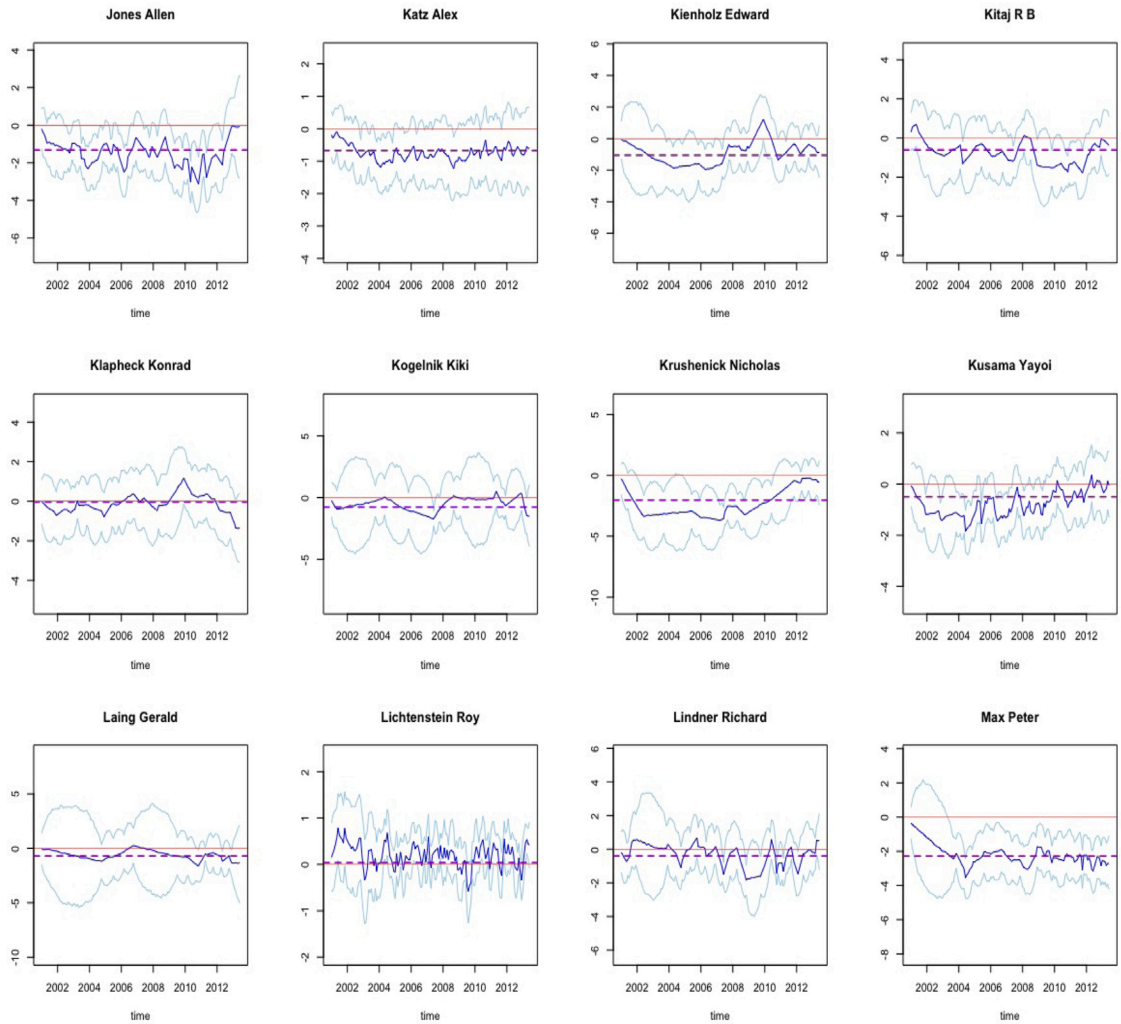

Fig. A.4. Posterior means (dark blue line) and 95% credible intervals (light blue lines) for the dynamic intercept and the dynamic coefficients for the artist-specific coefficients (blue lines) and OLS estimates (dotted line), across artists during the study period (2001–2013). Zero is provided as a reference with a solid red line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Blouin Art Database. Further description of the construction of each variable is provided in the body of the manuscript.

2014) on the estimated trajectories of the coefficients of the artists, and determining whether specific clusters of artists exist in the data (and the prices have substantially different behaviors).

The endogeneity problem can potentially appear in the context of time series analysis of causal processes. It is common for some factors within a causal system to be dependent for their value in period t on the values of other factors in the causal system in period $t-1$. The potential problem of endogeneity of time-varying coefficients would be an interesting topic to explore further. For instance, Kim (2008) shows a variety of time-varying models in this regard, and considers possible solutions. Extending a model that not only captures time dynamics as in this manuscript, but endogeneity, while outside of the scope of this manuscript, could be further studied.

Future research could also incorporate prior information or expert views in the Bayesian model. While we incorporated non-informative priors in the analysis, the proposed approach allows for information or parametric constraints to be easily incorporated. In the case of art auctions, one could use as such expert views the estimations put forth by auction houses prior to the auction date regarding the price that paintings are projected to attain. For example, prior to each auction, Christie's and Sotheby's offer, as part of the information for each lot to be auctioned, a range of prices (a minimum and a maximum) that a painting (or any other object to be auctioned) is expected to attain. These projected ranges could be used to construct more informative priors. There is also a reserve price set by the seller. The reserve price, which is unknown to buyers, may be below the minimum price. As expressed by Wheeler, Paez, Spinney, and Waller (2012), the incorporation of expert information into the Bayesian modeling framework is in line with the scientific method, where prior information that is available before gathering data is used together with observed data to inform what we now know (i.e., posterior distribution of the parameters).

Appendix

A.1. Model structure

At each time t, with $t = 1, \dots, T$ we observe a vector of auction prices on a set of n_t works. Let $\boldsymbol{y}_t = \left[\log(y_{1,t}), \dots, \log(y_{n_t,t})\right]'$ be the vector of the log prices of artworks auctioned at time t. Each vector $\boldsymbol{y}_t$ has a different size n_t. We develop a dynamic specification that allows a dynamic evolution of the individual coefficients. We write below the general specification, and then we explicitly define each component. We follow the general notation for Bayesian Dynamic Linear Models (DLM) specified in West and Harrison (1997). The model

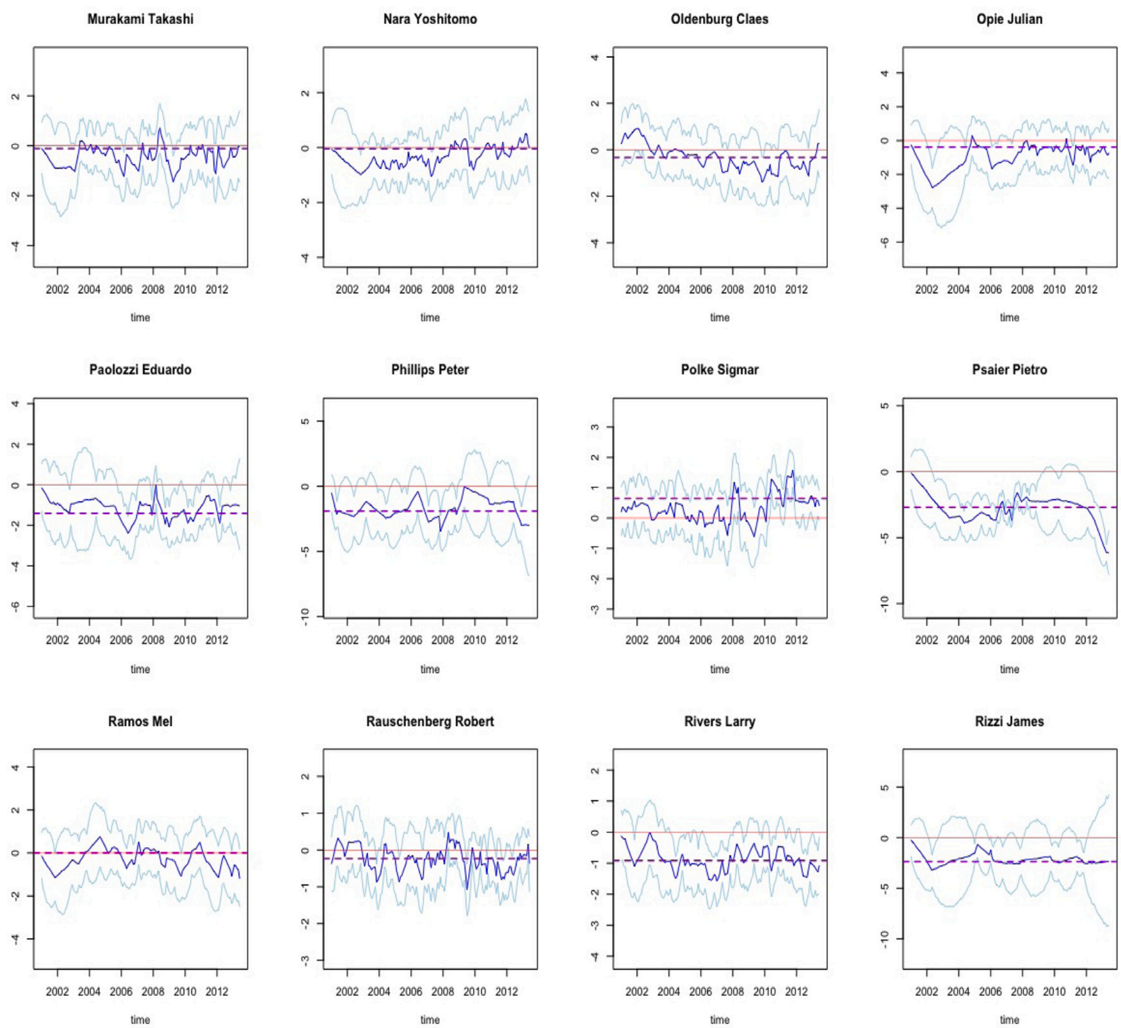

Fig. A.5. Posterior means (dark blue line) and 95% credible intervals (light blue lines) for the dynamic intercept and the dynamic coefficients for the artist-specific coefficients (blue lines) and OLS estimates (dotted line), across artists during the study period (2001–2013). Zero is provided as a reference with a solid red line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Blouin Art Database. Further description of the construction of each variable is provided in the body of the manuscript.

is formed by two equations: the observation (ob.eq.) and evolution (ev.eq.) equations:

$$\text{ob.eq. } \underset{n_t\times 1}{\boldsymbol{y}_t} = \underset{n_t\times p}{\boldsymbol{F}_t} \underset{p\times 1}{\boldsymbol{\theta}_t} + \underset{n_t\times 1}{\boldsymbol{v}_t} \tag{A.1}$$

$$\text{ev.eq. } \underset{p\times 1}{\boldsymbol{\theta}_t} = \underset{p\times p}{\boldsymbol{G}_t}\underset{p\times 1}{\boldsymbol{\theta}_{t-1}} + \underset{p\times 1}{\boldsymbol{w}_t} \tag{A.2}$$

$\boldsymbol{F}_t$ is the design matrix. Each row k contains the covariates of work k anchored at time t. It can be decomposed in several interpretable components. $\boldsymbol{F}_{k_t} = \left[1\boldsymbol{F}_{ck_t}\boldsymbol{F}_{Ak_t}\boldsymbol{F}_{sk_t}\right]$. The first term is the design value for a time-varying intercept.

- $\boldsymbol{F}_{ck_t}$ is the vector of q_c artwork characteristics $\left[x_{1k_t}, x_{2k_t}, \dots, x_{q_ck_t}\right]$. In our case it includes area, area squared, whether the work was signed, etc.
- $\boldsymbol{F}_{Ak_t}$ is the vector of binaries that indicates the artist who made that work.
- $\boldsymbol{F}_{sk_t}$ is the seasonal component design matrix. We use a trigonometric representation with pairs of harmonic components. Thus $\boldsymbol{F}_{sk_t} = [0, 1, 0, 1]$ for two harmonic components.
- $\boldsymbol{\theta}_t$ is the vector of state variables which can be decomposed as $\boldsymbol{\theta}_t = \left[\beta_{0t}, \beta_t, \alpha_t, s_t\right]$, where β_{0t} is the dynamic intercept, $\beta_t = \left[\beta_{1t}, \dots, \beta_{q_ct}\right]$ the time-varying regression parameters for the work characteristics, $\alpha_t = \left[\alpha_{1t}, \dots, \alpha_{qA}\right]$ the artist time-varying parameters, $s_t = \left[s_{1t}, s^\star_{1t}, s_{2t}, s^\star_{2t}\right]$ the seasonal state vector.
- $\boldsymbol{v}_t$ is an i.i.d observational error; $\boldsymbol{v}_t \sim N\left[0, V_t\right]$. In our case, for simplicity, we assume that $V_t = V$. The error variance V is structured with a standard inverse gamma $IG\left(a_V, b_V\right)$ distribution.

The evolution equation contains an evolution matrix $G_t = G = \text{blockdiag}\left[G_1, G_c, G_A, G_s\right]$, G_1, $G_c = \mathbb{1}_{qc}$, $G_A = \mathbb{1}_{qA}$, and

$$G_s = \begin{bmatrix} \cos(w_1) & \sin(w_1) & 0 & 0 \\ \sin(w_1) & \cos(w_1) & 0 & 0 \\ 0 & 0 & \cos(w_2) & \sin(w_2) \\ 0 & 0 & -\sin(w_2) & \cos(w_2) \end{bmatrix}$$

where w_i are the Fourier frequencies $w_i = \frac{2\pi i}{12}$. The evolution error $\boldsymbol{w}_t$ follows a multivariate normal with mean 0 and evolution variance $\boldsymbol{w}_t = W = \left[W_0, W_c, W_A, W_s\right]$, where $W_0 \sim IG\left[a_W, b_W\right]$, and

$$W_c = \begin{bmatrix} w_{c1} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & w_{cq_c} \end{bmatrix}$$

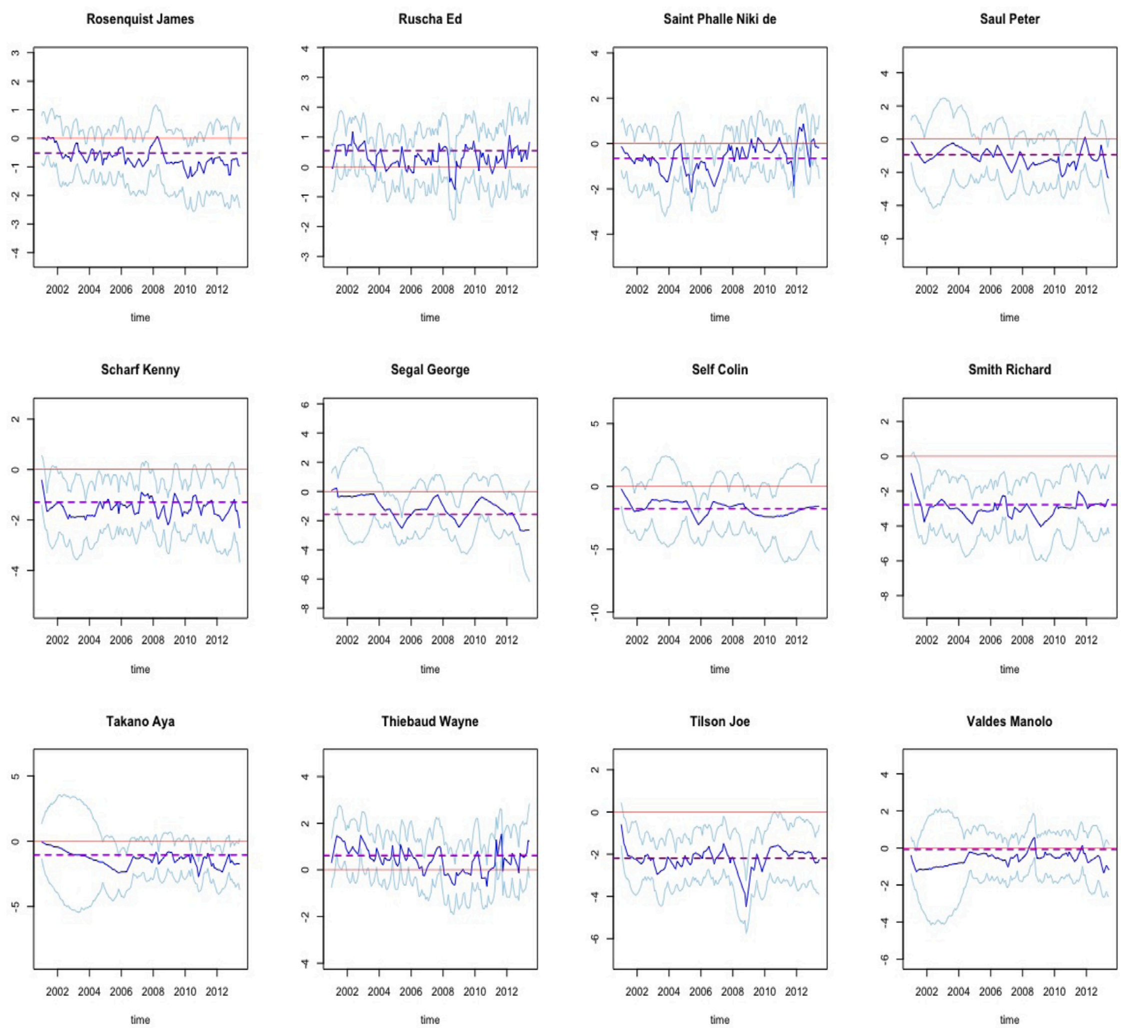

Fig. A.6. Posterior means (dark blue line) and 95% credible intervals (light blue lines) for the dynamic intercept and the dynamic coefficients for the artist-specific coefficients (blue lines) and OLS estimates (dotted line), across artists during the study period (2001–2013). Zero is provided as a reference with a solid red line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Blouin Art Database. Further description of the construction of each variable is provided in the body of the manuscript.

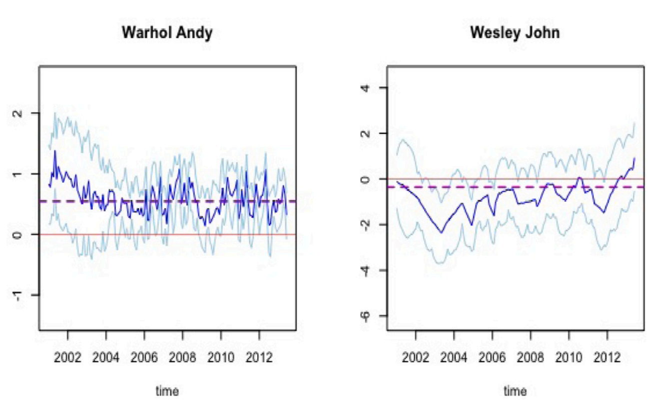

Fig. A.7. Posterior means (dark blue line) and 95% credible intervals (light blue lines) for the dynamic intercept and the dynamic coefficients for the artist-specific coefficients (blue lines) and OLS estimates (dotted line), across artists during the study period (2001–2013). Zero is provided as a reference with a solid red line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Blouin Art Database. Further description of the construction of each variable is provided in the body of the manuscript.

where $W_{c_i} \sim IG\left[a_W, b_W\right]$, for $i = 1, \dots, q_c$ and

$$W_A = \begin{bmatrix} w_{A1} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & w_{Aq_A} \end{bmatrix}$$

where $W_{A_i} \sim IG\left[a_W, b_W\right]$, for $i = 1, \dots, q_A$ and

$$W_s = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

The model is completed by normal priors for all the initial state variables.

A.2. Sampling

The estimation of the model is conducted in a Bayesian framework, and it requires a Markov Chain Monte Carlo (MCMC) algorithm. The Gibbs sampler involves two main steps, to sample the state variables $\boldsymbol{\theta}_t$ and the parameters $\{V, W\}$ from their respective full conditionals:

$$\underset{p\times 1}{m_t} = \underset{p\times 1}{a_t} + \underset{p\times n_t}{A_t} \underset{n_t\times 1}{e_t}$$

$$\underset{p\times n_t}{A_t} = \underset{p\times p}{R_t} \underset{p\times n_t}{\boldsymbol{F}_t} \underset{n_t\times n_t}{Q_t^{-1}}$$

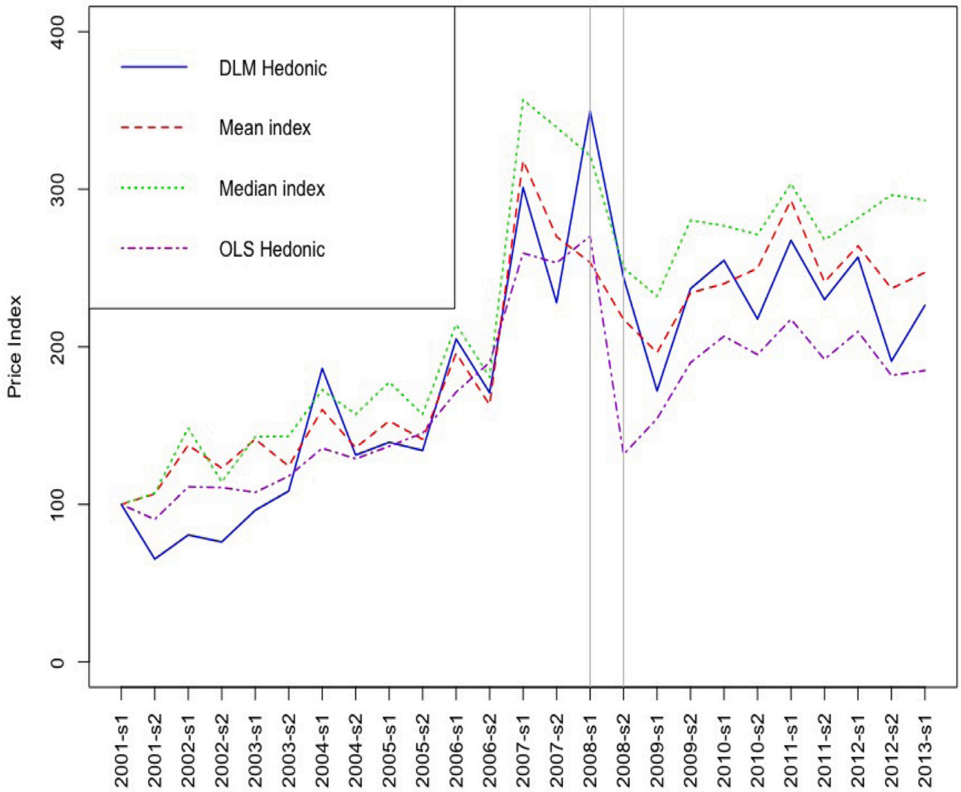

Fig. A.8. Evolution of Pop-Art Price Index (Semiannual, 2001–2013) for the different estimation methods. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Blouin Art Database. Further description of the construction of each line is provided in the body of the manuscript.

$$\underset{p\times p}{C_t} = \underset{p\times p}{R_t} - \underset{p\times n_t}{A_t}\,\underset{n_t\times n_t}{Q_t}\,\underset{n_t\times p}{A_t^T}$$

$$\underset{p\times 1}{a_t} = \underset{p\times p}{G_t}\,\underset{p\times 1}{m_t}$$

$$\underset{n_t\times 1}{e_t} = \underset{n_t\times 1}{\boldsymbol{y}_t} - \underset{n_t\times 1}{f_t}$$

$$\underset{p\times p}{a_t} = \underset{p\times p}{G_t}\,\underset{p\times p}{C_t}\,\underset{p\times p}{G_t^T} + \underset{p\times p}{W_t}$$

$$\underset{n_t\times n_t}{a_t} = \underset{n_t\times p}{\boldsymbol{F}_t}\,\underset{p\times p}{R_t}\,\underset{p\times n_t}{\boldsymbol{F}_t} + \underset{n_t\times n_t}{V\mathbb{1}_{n_t}}$$

$$\underset{n_t\times 1}{f_t} = \underset{n_t\times p}{\boldsymbol{F}_t^T}\,\underset{p\times 1}{a_t}$$

The estimation includes backward sampling, where $(\theta_t|\theta_{t-1})$ for $t = T-1, \ldots, 1$

- $(\theta_t|\theta_{t+1}) \sim N\left[h_t, H_t\right]$
- $\underset{p\times 1}{h_t} = \underset{p\times 1}{m_t} + \underset{p\times p}{B_t}(\underset{p\times 1}{\theta_t} - \underset{p\times 1}{a_t})$
- $\underset{p\times p}{H_t} = \underset{p\times p}{C_t} - \underset{p\times p}{B_t}\,\underset{p\times 1p}{R_{t+1}}\,\underset{p\times p}{B_t}$
- $\underset{p\times p}{B_t} = \underset{p\times p}{C_t}\,\underset{p\times p}{G_t}\,\underset{p\times p}{(R_{t+1})^{-1}}$

sample $(V, W|Y, \theta_t)$ and sample $V \sim IG\left(a_V + n/2, \frac{\sum_{t=1}^{T}(y_t - \boldsymbol{F}_t\theta_t)^T(y_t - \boldsymbol{F}_t\theta_t)}{2}\right)$ where n is the total number of observations. Each element of W will be sampled from an IG distribution. Each parameter will be sampled independently from $W_i \sim IG\left(a_W + T/2, b_W + \frac{\sum_{t=1}^{T}(\theta_t - \boldsymbol{G}_t\theta_{t-1})^T(\theta_t - \boldsymbol{G}_t\theta_{t-1})}{2}\right)$

The model is extremely well-behaved in terms of convergence of the Markov Chains. We can obtain excellent results with no autocorrelation with as little as 1,500 iterations (500 burn in) leading to 1,000 effective samples and no necessity of thinning. For the results reported in the manuscript, we ran the chains even longer for consistency: 11,000 iterations, 1,000 burn in, thinning of 10%, leading to 1,000 effective samples. We used very diffuse priors N(0, 100), and IG(0.1,0.1) for the variance components, but explored in a sensitivity analysis other options, which yielded similar results. Since our dataset is large the impact of the priors is minimal and so the estimates are robust and do not change significantly when choosing different priors.

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