Emotional Yields of Collectibles*

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Abstract

We propose a novel method to estimate emotional yields of collectibles based on factor mimicking portfolios. Using up to 110 years of collectibles returns for 13 distinct asset classes, we apply machine learning techniques to address challenges from non-synchronous trading. We use these estimates to study how emotional yields affect equilibrium pricing. Emotional yield estimates for 24 of our 30 collectibles return series are positive, with an annualized mean (median) of 2.64% (2.53%). Despite various forms of underestimation, these results provide evidence that assets with positive emotional returns have lower equilibrium financial returns.

Keywords: collectibles; emotional dividend; non-pecuniary returns; alternative investments; factor-mimicking portfolios.

*Initial title: "Convenience Yields of Collectibles."

1 Introduction

Investors sometimes accept lower financial returns in exchange for non-pecuniary utility.[1] We present long-horizon evidence of this equilibrium tradeoff in collectibles markets, where emotional benefits—private enjoyment and social signaling—are of first-order importance, assets are illiquid, and time series are long. Using factor-mimicking portfolios of liquid securities, we estimate the emotional yield embedded in 30 return series across 13 collectible categories over up to 110 years, and we find that most series exhibit positive emotional yields (mean about 2.5% p.a.).

Our primary contribution is to the pricing of unique, illiquid assets and to the measurement of non-pecuniary returns. We use ESG as an analogy—another setting where investors may trade off financial return for non-financial utility—without making claims about ESG returns per se. This framing aligns the empirics with the argument while preserving the broader theoretical relevance of an equilibrium utility–return tradeoff.

In surveys, individual investors report sizable non-financial benefits from sustainable investing (Riedl & Smeets 2017; Bauer, Ruof, & Smeets 2021). Yet the price impact of such preferences appears limited. For example, green bonds trade at small premia (2 bps in Zerbib 2019; 5-19 bps in Baker et al. 2022). Studying the effect of emotional dividends on equilibrium pricing is challenging not only because of the confounding effects of changing tastes and hedging demand, but also because widespread interest in sustainable investing is a recent phenomenon, leading to a short time horizon for price investigation.

To study the role of emotional dividends in equilibrium pricing, researchers need an instrument that is largely insulated from changing tastes and hedging demands and has a sufficiently long time series. We seek to overcome these obstacles by using returns data for 13 distinct types of collectibles spanning 110 years. This data helps us answer two primary questions. First, how should emotional returns be estimated? Second, do emotional returns influence prices in equilibrium?

The market for collectibles has a long history. Assets such as art, wine, and stamps have been popular investments for centuries. Importantly, and in part due to the relative

[1] We use the term "emotional yield" to denote the non-pecuniary utility from ownership (enjoyment, signaling). This concept is analogous to what we previously referred to as a "convenience yield," but we adopt the new term to avoid confusion with its standard meaning in commodities and safe-asset markets (functional inventory or liquidity services inferred from arbitrage relations). Our estimates pertain to non-pecuniary utility in unique, illiquid assets.

illiquidity of their markets, collectibles are more insulated from changing tastes and hedging demands. Instead, demand for collectibles originates with the emotional dividends associated with either viewing the object (Goetzmann, Mamonova, & Spaenjers 2015; Lovo & Spaenjers 2018) or signaling one's wealth (Mandel 2009). These features of collectibles and collectibles markets provide a natural setting for studying emotional dividends.

We construct a broad database of collectibles, 30 distinct return series covering 13 categories: paintings, prints, photographs, drawings, sculptures, stamps, coins, furniture, rugs, jewelry, wine, classic cars, and violins. For some categories, we have multiple measures of the returns, which vary both in terms of the underlying (eg, English coins vs. US coins) and the time horizon (eg, annual 1901-2007 vs. quarterly 1997 – 2018).

Our measure of emotional yields is grounded in a factor mimicking portfolio paradigm. At each date, investors choose between a diversified collectibles portfolio and a factor-matched portfolio of liquid securities. Assuming investors are risk-neutral, then in equilibrium, the conditional expected returns of the collectibles portfolio and the factor mimicking portfolio will be equal. While the factor mimicking portfolio of liquid securities has only a financial return component, the collectibles portfolio has both financial and non-financial return components. Explicitly measuring the financial returns of the collectibles and the factor mimicking portfolio, we can impute the non-financial return, which is the emotional yield.

We construct collectibles factor mimicking portfolios in the spirit of Roll & Srivastava (2018). The basic multiple-factor paradigm stipulates that the return on any asset, for example collectibles portfolio j, can be written as a linear function of pervasive factors f:

$$R_{j,t} = \alpha_j + \beta_{j,1} f_{1,t} + \beta_{j,2} f_{2,t} + \cdots + \beta_{j,K} f_{K,t} + \epsilon_{j,t}. \tag{1}$$

$R_{j,t}$ denotes the return on asset j in period t, and α_j is the intercept. The β's are the factor sensitivities. The factor mimicking portfolio of liquid securities matches the factor sensitivities (β's) of the collectibles portfolio while also minimizing the residual variance (ie: idiosyncratic risk).

Our implementation extends beyond the Roll & Srivastava (2018) approach to address several empirical challenges. First, collectibles returns are highly autocorrelated from non-synchronous trading and so standard coefficient estimators for the β's are unreliable (eg: Scholes & Williams 1977, Dimson 1979). We use the Dimson (1979) "aggregated coefficients" method to estimate autocorrelation-consistent loadings and guard against overfitting with machine learning methods (eg: lasso, ridge, partial least squares). Second, we generalize the factor mimicking portfolio procedure to relax the assumption that the basis assets of our factor mimicking portfolios have orthogonal residuals in equation (1). Last, we adapt the procedure to consider practical implementation, adding a short-sales constraint for the mimicking portfolio's constituents and formalizing the tradeoff between better matching factor exposures and minimizing the mimicking portfolio's idiosyncratic risk.

In this study, our pervasive factors are principal components (PCs) estimated from 18 countries' stock and bond total return indices. The first ten PCs explain 90% of the total variation. Our mimicking portfolio basis assets are drawn from 57 stock and bond return indices from across these 18 countries. We use stock and bond indices from around the world to construct our PCs and form mimicking portfolios because collectibles are traded globally. We consider a multitude of implementation variations, and use measures of factor mimicking portfolio quality to standardize the process for choosing the best implementation. These variations consider, for example, whether to use the first five or ten PCs as factors, and whether the basis assets should include both stocks and bonds or only stocks.

Because tastes likely evolve but are difficult to model (e.g., Goetzmann et al. 2021), we do not estimate time-varying emotional returns period-by-period. Instead, we form mimicking portfolios over the full sample, relying on the weaker assumption that tastes are approximately stable in the long run. Our emotional yield estimates are therefore unconditional expectations.

Our results show that most collectibles carry a positive average emotional yield. 24 of the 30 return series have positive point estimates, and 14 of these are statistically significant. Moreover, the mean and median annualized emotional yield estimates are large, 2.64% and 2.53% respectively. Notably, the power of our tests are unusually limited because the emotional yields inherit the autocorrelation of the collectibles returns – correcting for the autocorrelation reduces our effective sample size.

These large estimated effect sizes are conservative for at least four reasons. First, the mimicking portfolios reduce residual volatility by 1–30 percentage points and risk-averse investors would value this, raising implied emotional yield. Second, we ignore collectible transaction costs, which show up explicitly in our emotional yield formula as a positive additive term. Collectibles transaction costs are material but challenging to estimate. Third, we do not adjust for the greater liquidity of the mimicking portfolios – as a result, we understate the attractiveness of the mimicking portfolio and so underestimate the emotional yield. Last, repeat-sales price indices are upward-biased, overstating financial returns on collectibles and thus understating emotional yield. Given that our estimated emotional yields are underestimated but still generally positive and material, it seems that emotional yields are priced in equilibrium.

Our study makes several primary contributions. First, we show that emotional dividends are priced in equilibrium and are associated with lower financial returns. This contributes to the debate on whether and how investors can "do well by doing good." The Pastor, Stambaugh, & Taylor (2021) theory proposes that, in equilibrium, sustainable investments underperform because of compensatory emotional dividends, although a variety of other factors can lead to transitory outperformance. Our results provide empirical evidence that emotional dividends are priced in equilibrium, lowering the financial return quite meaningfully compared to investments with commensurate systematic risk and no emotional dividends. This is important because asset managers often market sustainable investments as offering superior risk-adjusted returns,[2] which our evidence suggests is not the case. Other work suggests there is – or may be – a tradeoff between sustainability and financial returns (eg: Orlov, Ramelli, & Wagner 2022; Starks 2023), although it does not establish the financial tradeoff explicitly.

Second, we devise a new method for estimating non-financial dividends. While many papers consider non-financial dividends for collectibles theoretically,[3] few attempt to estimate them. Those that do focus on rental yields (Atukeren & Seckin 2007), factor model alphas (Hodgson & Vorkink 2004), hedonic price regressions (Hughes 2022; Dobrynskaya & Bianchi 2023), and assumptions about how the level of financial returns relates across asset classes (Stein 1977). Our approach aims to be more general, with fewer assumptions, and more widely applicable. Estimating non-financial value – whether genuine convenience

[2]For example, State Street Global Advisors (2018) claim "ESG [is] a source of alpha that could lead to positive portfolio performance over time." Allianz Global Investors (2019) argues that ESG is "a 'plus' for sustainability [and] may also result in a 'plus' for performance." Capital Group (2021) claims that "improvements in ESG performance can ultimately translate into superior returns." JP Morgan (2020) claims that the "systematic inclusion of financially material ESG factors...[supports their] goal of enhancing long-term risk-adjusted financial returns."

[3]For example, Goetzmann & Spiegel (1995), Mandel (2009), Goetzmann, Mamonova, & Spaenjers (2015), and Lovo & Spaenjers (2018) assign an important theoretical role to collectibles' emotional dividends for valuation. Notably, Jovanovic (2013) and Dimson, Rousseau & Spaenjers (2015) examine whether wines that are associated with high emotional dividends generate lower financial returns.

yields or non-pecuniary benefits – has also gained recent attention in other markets like Eurozone debt (Jiang et al. 2025), US Treasuries (van Binsbergen, Diamond, & Grotteria 2022), green bonds (Zerbib 2019; Baker et al. 2022; Pastor, Stambaugh, & Taylor 2022), and explicitly sustainable investment funds (Barber, Morse & Yasuda 2021; Laudi, Smeets, & Weitzel 2025; Van der Beck 2025). Estimating emotional yields for collectibles entails additional complexity but has similar intuition.

Third, we create a factor mimicking portfolio framework that can be applied to a variety of private value assets. Goetzmann, Spaenjers, & van Nieuwerburgh (2021) find that the value of these assets is significant, with collectibles in the US comprising at least $5.5 trillion. Their estimates are based only on jewelry, fine art, antique furniture, and classic cars, and there are many other types of collectibles that have garnered great interest. Our framework is also relevant for some types of real assets. For example, Andonov, Kraussl, & Rauh (2021) find that public institutional investors' unusually large commitment to underperforming infrastructure projects is driven by ESG considerations. In addition to using factor mimicking portfolios for estimating emotional yields, they also have more immediate practical applications. Investors can apply our technique to obtain investment exposure to a portfolio of real and private value assets while owning only liquid securities and diversifying away idiosyncratic risk.

Collectibles have been increasingly financialized via fractionalized ownership platforms (e.g., Masterworks; Rally), where investors purchase securitized shares in individual artworks/collectibles but do not receive possession or display rights; in parallel, art-secured lending has grown into a multi-billion market (estimated at $21–24bn in outstanding loans in 2019), and a corporate art-leasing segment rents works for display. In these settings, the emotional dividend cannot be monetized by shareholders or lenders, so the expected return shortfall relative to a liquid factor-matched alternative—the emotional yield—is directly decision-relevant. This shift parallels broader lifestyle trends: even among the wealthy, the number of U.S. millionaire renters has more than tripled since 2019, reflecting a preference for liquidity and flexibility over ownership—a pattern that may extend to cultural assets as leasing markets mature.

Our paper is organized as follows: Section 2 reviews the related literature; Section 3 describes our data; Section 4 presents our empirical strategy for estimating emotional yields for collectibles; Section 5 discusses our empirical results; Section 6 discusses robustness; and

Section 7 concludes. Additional empirical results and estimation details are located in the Online Appendix, which is available on the authors' websites.

2 Related Literature

To provide additional context, we briefly review two literatures: collectibles and the relation between sustainable investing and non-pecuniary benefits.

Concentrated academic interest in collectibles spans many markets: art (Goetzmann, Renneboog & Spaenjers 2010; Renneboog & Spaenjers 2013), cars (Laurs & Renneboog 2019; Le Fur 2023), wine (Dimson, Rousseau, & Spaenjers 2013), stamps (Dimson & Spaenjers 2011), fine pens (Tomkovick & Dobie 1995), violins (Graddy & Margolis 2011), coins (Obaid, Pukthuanthong, & Maslar 2020), trading cards (Hughes 2022), collectible sneakers (Soo 2021), NFTs (Dobrynskaya & Bianchi 2023), and rare books (Ursprung 2020, 2021). Many collectibles derive value from their authenticated uniqueness (Dobrynskaya & Bianchi 2024; Li, Ma, & Renneboog 2024). The burgeoning NFT market has provided a useful laboratory to show that pricing is about more than just speculative flipping (Penasse & Renneboog 2022; Chava, Hu, & Paradkar 2025). Hedonic regressions on the Cryptopunks NFT collection reveal strong aesthetic preferences influencing pricing (Alsultan, Kourtis, & Markellos 2024), and lab experiments find that individuals attach a high willingness to pay to social value, which includes being connected to a community of similar enthusiasts (Hofstetter, Fritze, & Lamberton 2024).

Measuring returns is challenging because objects are unique and trade infrequently. Collectibles price indices are constructed using either repeat-sales regression, which exploits multiple sales of the same work, or hedonic regression, which exploits similar characteristics across works. A growing trend is to use machine-learning-based hedonic regression to construct price indices – as in Aubry et al. (2023), Algieri et al. (2024), and Sagarra, Vici, & Zanola (2025) – although the high data requirements lead to short time series. In characterizing the returns to collectibles, many studies find that collectibles have higher average returns than bonds and bills but lower average returns than stocks. Many investors find collectibles attractive for their portfolio diversification benefits (Vorsatz 2020).

Physical collectibles – in contrast to digital collectibles like NFTs – are also unusual for their very high transaction costs (Campbell 2008; Dimson & Spaenjers 2011; Kraussl &

Nasser Eddine 2018). Round-trip transaction costs are often on the order of 20-30% of the sales price. Likely a consequence, physical collectibles are infrequently traded, with average holding periods believed to be between 28 years (Mei & Moses 2002) and 40 years (Reitlinger 1961).

We relate collectibles to sustainable investing since emotional dividends are important for both. Empirically, investors' preference for ESG has been well documented. Bialkowski & Starks (2016) find that inflows to socially responsible investment (SRI) funds are higher than inflows to comparable non-SRI funds. Relatedly, Hartzmark & Sussman (2019) find that mutual funds with the highest Morningstar sustainability rating receive abnormally large flows. Bollen (2007), Renneboog, ter Horst, & Zhang (2011), and Glossner et al. (2025) show that flows to sustainable funds are more resilient in the face of systematic shocks and negative performance. Some studies corroborate these results with surveys. Riedl & Smeets (2017) find investors in SRI funds expect lower returns and are willing to pay higher management fees, with the forgone financial performance driven by social preferences and social signaling. Bauer, Ruof, & Smeets (2021) find that a majority of Dutch pension participants vote in favor of redirecting pension investments towards more sustainable goals, even if it leads to lower financial performance.

Pastor, Stambaugh, & Taylor (2021) provide a framework for thinking about how preferences for ESG investing relate to expected returns in equilibrium. Their model predicts that agents with stronger ESG preferences earn lower expected returns because they derive utility from their holdings. Importantly, they sacrifice less financial return than they are willing to, which suggests our emotional yield estimates serve as a lower bound. While emotional dividends are associated with lower equilibrium financial returns, they show theoretically that green assets can temporarily outperform if: (1) tastes unexpectedly become greener; or (2) a green-related risk emerges (eg: climate change worsens unexpectedly).

Empirically, results are mixed—as expected when multiple forces operate. A broad review finds mostly non-negative return relations (Friede, Busch, Bassen 2015), but other work is mixed (Gillan, Koch, Starks 2021). Earning non-financial utility should lower *equilibrium* financial returns as proposed theoretically by Pastor, Stambaugh, & Taylor (2021) and empirically supported by our results. However, temporarily higher financial returns can be driven by other factors like changing tastes (Fama & French 2007), unexpected risk realizations (Pastor, Stambaugh, & Taylor 2022), unrecognized employee loyalty or good governance mechanisms (Edmans 2011), reduced exposure to environmental liability risks (Li et al. 2024; Bellon 2025), or an unappreciated link between high sustainability and higher future profits (Albuquerque, Koskinen, & Zhang 2019; Pedersen, Fitzgibbons, & Pomorski 2021). Consistent with lower required returns, more sustainable firms often exhibit lower systematic risk and cost of capital (Chava 2014; El Ghoul et al. 2011; Albuquerque et al. 2018; Fatica & Panzica 2024; Hoepner et al. 2024).

Several additional studies are consistent with our results but find a meaningfully smaller effect. Focusing on the market for green bonds, the "greenium," or lower annual yield on green bonds relative to their non-green counterparts, is typically small, estimated at 2 bps in Zerbib (2019), 5-19 bps in Baker et al. (2022), and 0-4 bps in Pastor, Stambaugh, & Taylor (2022). Our results are an order of magnitude larger, with a median of 253 bps per year. These differences may be driven by clientele effects as well as hedging considerations. Alternatively, the benefits of greenness may simply be small or highly uncertain, which could stem from concerns about greenwashing (Duchin, Gao, & Xu 2024; Inderst & Opp 2025) or firms shifting brown activities out of immediate sight (Feldhütter & Pedersen 2025).

3 Data

We construct a comprehensive database of collectibles returns as well as multi-country stock returns and bond yields spanning 110 years at different frequencies. This enables us to study emotional yields for a variety of collectibles assets.

Our collectibles data is from a variety of academic studies and private organizations. Our 30 distinct data series span 13 categories: paintings, prints, photographs, drawings, sculptures, jewelry, stamps, coins, wine, classic cars, violins, furniture, and rugs. The basket of collectibles underlying each price index is fundamentally unique. For example, 5 series focus on distinct categories of paintings, namely British paintings, blue-chip paintings, global paintings, paintings by popular artists, and paintings by the average artist. 6 of the 30 price indices are denominated in GBP and the rest are denominated in USD. For consistency, we convert all indices into a common currency (USD).[4]

To summarize our results, we sort our collectibles into three categories: public-domain collectibles, specialist-domain collectibles, and private-domain collectibles. These categories

[4]The annual wine & British art price indices are denominated in deflated GBP, so prior to currency conversion, we "reflate" the returns using realized UK CPI inflation from Global Financial Data (GFD).

reflect which types of individuals are able to appreciate the collectible's value, which is important for signaling and enjoyment within social networks. Public-domain collectibles include fine art (paintings, sculptures, prints, photographs, and drawings) and jewelry, which are featured and showcased in many public venues. These items can be personally enjoyed and also used for signaling with a general audience. Specialist-domain collectibles include violins, stamps, coins, wine, and classic cars, which are often enjoyed by close-knit collector communities or specialists. These items can be personally enjoyed, but only serve a signaling purpose for a limited audience who will appreciate, for example, the 1794 Flowing Hair Silver Dollar.[5] Last, private-domain collectibles include antique furniture and fine rugs & carpets, which are generally admired in one's home and so derive most of their value from personal enjoyment and not signaling. We equal-weight the assets in each of these three categories to form summary statistics for groupings of similar collectibles, making slight adjustments to avoid over-weighting assets with multiple price indices.[6]

We collect data from academic studies including Goetzmann, Renneboog, & Spaenjers (2011) for British paintings & drawings, Dimson & Spaenjers (2011) for blue-chip British stamps, Dimson, Rousseau, & Spaenjers (2015) for blue-chip wine, Graddy & Margolis (2011) for violins, and Maslar, Obaid, & Pukthuanthong (2020) for US coins. We also collect data from private organizations including Sotheby's for blue-chip paintings, Artprice.com for global fine art price indices, Art Market Research for price indices across many asset categories, Liv-ex for their market price-based wine index, and Greysheet for coin data.

Table 1 provides descriptions of the 30 collectibles price indices. Notably, they suffer from a variety of estimation biases. First, the 21 repeat-sales price indices suffer from selection bias, as collectibles with greater price appreciation are more likely to trade (Goetzmann 1993; Korteweg et al. 2015). In particular, repeat-sales price indices are biased upward because they do not include works that fail to sell at auction (Anderson et al. 2016). At the same time, the 9 average-sales price indices fail to control for quality.[7] Second, many

[5]This is America's first minted silver dollar. Of 1,748 Flowing Hair dollars issued by the US Mint in 1794, only 140-150 survive today. A well-preserved specimen sold at auction for $10.0 million in 2013.

[6]For annual data, we simply equal-weight the return series within each category as there is no duplication. For quarterly data, we equal-weight the specialist-domain return series and the private-domain return series. In contrast, the public-domain series feature great multiplicity. We first compute three equal-weighted sub-indices of global fine art (paintings, prints, sculptures, photographs, and drawings), popular fine art (popular artist paintings and popular Euro-American sculptures), and jewelry (jewelry and diamonds) and then compute the public-domain series as the equal-weighted average. The monthly series are treated identically to the quarterly series.

[7]To mitigate the effect of the tails on the average, Art Market Research includes only the central 80% of sales prices for each month, meaning the top 10% and bottom 10% of monthly prices are omitted.

of the indices suffer from varying degrees of look-ahead bias. For example, the Sotheby's Mei-Moses index is based on paintings that sold at Sotheby's or Christie's post-1950, and for which a prior public auction could be identified from the artwork's provenance. As Sotheby's & Christie's are the premier art auction houses, these paintings are selected on the basis of being "blue chip" in the post-1950 time period, which almost surely inflates the estimated returns. Similarly, the Art Market Research popular artist paintings index is backdated using artists that were later determined to be popular. Selection biases affect many of our indices to differing degrees, and also play a role in determining the types of collectibles price indices available to us for analysis.

To make our returns data more comparable, we standardize the time horizons: annual data is 1901 - 2007 and quarterly data is Q1 1998 - Q3 2018. The only exceptions are US coins (1968-2007), blue-chip classic cars (1981-2007), and diamonds (Q3 2004 - Q4 2017). The monthly data is compounded to a quarterly frequency for our main analysis, although we consider the monthly frequency for robustness in the Online Appendix.

Table 2 provides summary statistics for the return series. A common feature of the returns data is autocorrelation, which is sometimes quite strong. This is because collectibles are infrequently traded, leading the returns to be autocorrelated and appear smoothed. In particular, this leads standard estimators to underestimate the true variance (Andersen et al. 2017) and misestimate the covariance (Scholes & Williams 1977; Dimson 1979).

In Table 3, we provide autocorrelation-adjusted and unadjusted estimates of the geometric average return, standard deviation, and total return. Our autocorrelation adjustment procedure for these summary statistics follows Vorsatz (2020) and is summarized in the Online Appendix. Underestimating the standard deviation has a dramatic effect on the reported geometric average return. For example, the unadjusted annual geometric average return for US coins is 10.1%, but after adjusting the standard deviation from 22.2% to 32.0%, the geometric average return falls to 7.4%.[8]

Figures 1 & 2 plot the cumulative log returns for our collectibles for the annual and quarterly time horizons. Figure 1 shows the cumulative log returns of Public collectibles is much higher than that of Specialist collectibles. Blue-chip paintings have the highest returns and drive the returns of Public collectibles. We observe a sharp drop in returns around 1950

[8] A common approximation is that the geometric average return is equal to the arithmetic average return minus half of the variance. As the variance directly enters this equation, we see how underestimated variances lead to overestimated geometric average returns.

and in the early-to-mid 1990's. Figure 2 shows the returns of Specialist collectibles are higher than Public collectibles, and these are both much higher than Private collectibles. The relation between Public and Specialist collectibles is the opposite of the pattern presented in Figure 1. Notably, there is a systematic drop in returns in the late 2000's during the Subprime Mortgage Crisis. The English coins and classic cars generate the highest returns and drive the returns of Specialist Collectibles.

Despite these salient observations, we cannot read too much into the results in Figures 1 & 2. The previous discussion implies that the cumulative log returns in these figures are overestimates (sometimes substantially) of the true cumulative log returns that could have been obtained through a diversified buy-and-hold strategy in these asset classes. In addition, heterogeneity in the severity of autocorrelation (Table 3) means that different corrections need to be applied to the different indices, making comparisons across asset classes on the basis of the total return plots challenging.

We supplement our collectibles returns with international stock index returns for 18 countries: Australia, New Zealand, US, Denmark, Canada, South Africa, Ireland, Germany, UK, India, France, Belgium, Sweden, Japan, Netherlands, Finland, Switzerland, and Italy. We also use corporate & government bond yields from these countries whenever available; there are as many as 39 distinct yield series for the most recent time periods. All of these series are from Global Financial Data (GFD) and reported in the Online Appendix.

We construct principal components (PCs) of stock and bond returns and retain the first 5 or 10 principal components as pervasive factors. The ten PCs are the eigenvectors that explain about 90 percent of eigenvalues.

4 Empirical Strategy

Our empirical strategy proceeds in three steps. First, we theoretically motivate a measure of emotional yields in a factor mimicking portfolio (FMP) paradigm. Second, we generalize the traditional FMP estimation framework of Roll & Srivastava (2018) to allow for residual correlation and to formalize the tradeoff between minimizing residual variance and minimizing factor exposure matching error. We also introduce a short-sales constraint on the mimicking portfolio weights to better reflect the typical investor's portfolio problem. Last, we adapt the factor estimation procedure to account for unique features of collectibles returns, namely their autocorrelation from non-synchronous trading. Our goal is explanatory (in-sample factor replication), not predictive.

4.1 Estimating Emotional Yields

We decompose total realized collectibles returns as:

$$\underbrace{R^C_{t+1}}_{\text{Total Collectible Return}} = \underbrace{R^F_{t+1}}_{\text{Financial Return}} + \underbrace{R^E_{t+1}}_{\text{Emotional Return}} - \underbrace{R^T_{t+1}}_{\text{Transaction/Holding Costs (\%)}} \tag{2}$$

$$\implies \mathbb{E}_t[R^C_{t+1}] = \mathbb{E}_t[R^F_{t+1}] + \mathbb{E}_t[R^E_{t+1}] - \mathbb{E}_t[R^T_{t+1}] \tag{3}$$

In equilibrium, investors trade each period t so that expected total collectible returns are equal to the expected return on the factor mimicking portfolio:

$$\mathbb{E}_t[R^C_{t+1}] = \mathbb{E}_t[R^{FMP}_{t+1}] \tag{4}$$

The challenge in forming this FMP is in setting $\beta^k_{C,t} = \beta^k_{FMP,t}\ \forall k$ because the total collectible return is unobservable. These β terms represent the factor exposures of the collectible portfolio (C) and the factor-mimicking portfolio (FMP) to the k-th pervasive factor. One might be tempted to instead set $\beta^k_{F,t} = \beta^k_{FMP,t}\ \forall k$, that is, replace the total collectible return with the collectible's financial return. However, an important implicit assumption in doing so is that the betas for E and T are zero at each date t, which is unlikely to hold. For example, Mandel (2009) proposes that art provides a constant utility dividend and so functions as insurance, which implies that $\beta_{E,t} < 0$ during recessions. Instead, we note that:

$$\overset{\text{by Eq (3)}}{\implies} \mathbb{E}_t[R^E_{t+1}] = \mathbb{E}_t[R^C_{t+1}] - \mathbb{E}_t[R^F_{t+1}] + \mathbb{E}_t[R^T_{t+1}] \tag{5}$$

$$\overset{\text{by Eq (4)}}{\implies} \mathbb{E}_t[R^E_{t+1}] = \mathbb{E}_t[R^{FMP}_{t+1}] - \mathbb{E}_t[R^F_{t+1}] + \mathbb{E}_t[R^T_{t+1}] \tag{6}$$

$$\overset{\text{by LIE}}{\implies} \mathbb{E}[R^E_{t+1}] = \mathbb{E}[\mathbb{E}_t[R^E_{t+1}]] = \mathbb{E}[R^{FMP}_{t+1}] - \mathbb{E}[R^F_{t+1}] + \mathbb{E}[R^T_{t+1}] \tag{7}$$

We cannot form the conditional FMPs without very strong assumptions, and so cannot hope to estimate the conditional expectations in Equation (6). However, if we assume that the betas for C and F are very similar over long periods of time, then we can estimate the unconditional expectations in Equation (7). To be precise, we use the betas estimated on the collectibles financial return to construct $\mathbb{E}[R^{FMP}_{t+1}]$, and we estimate $\mathbb{E}[R^F_{t+1}]$ as the time-series average of the collectibles financial return. Our key assumption is equivalent to assuming that the betas for emotional returns and transaction/holding costs are close to zero on average.[9] It seems reasonable to assume that art enjoyment and risk factor returns are roughly uncorrelated on average, and similarly, that insurance or storage costs and risk factor returns are roughly uncorrelated on average.

Our identifying restriction concerns unconditional, long-run averages of non-pecuniary ("emotional") and cost components, not period-by-period or state-contingent relations. In models where viewing, ownership, and status utilities are private-value dividends (non-traded) rather than compensation for aggregate risk, their average covariance with traded risk factors is expected to be close to zero over very long horizons, even if short-run asymmetries exist. This implies a clear bias direction: if the emotional or cost components have negative average covariance with priced factors (e.g., stronger disutility in recessions), the collectible's observed financial return will be lower than that of its factor-matched alternative for a given exposure, so our emotional yield is biased downward (i.e., conservative).

The same logic applies to liquidity/transaction-cost advantages of the factor-mimicking portfolio (FMP), which further increase the FMP's attractiveness and thus raise the implied emotional yield. Consistent with our unconditional focus, simple descriptive checks—rolling correlations of emotional yields with inflation and wartime dummies—are small and do not alter conclusions (Appendix Figures A8 and A10; Tables A11, A12, and A13). We leave explicit modeling of time-varying or state-dependent loadings to future work.

4.2 Factor Mimicking Portfolio Framework

Factor mimicking portfolios use liquid securities ("basis assets") to match the factor structure of a target asset in a way that minimizes residual volatility, which in the multi-factor paradigm is uncompensated risk.

The basic multiple-factor paradigm stipulates that the return on any asset, say stock j observed over an interval ending at time t, can be written as a linear function

$$R_{j,t} = \alpha_j + \beta_{j,1} f_{1,t} + \beta_{j,2} f_{2,t} + \cdots + \beta_{j,K} f_{K,t} + \epsilon_{j,t} \tag{8}$$

where the f's denote the pervasive risk factors while the β's are factor sensitivities. We use

[9]This assumes average loadings on emotional returns and costs about 0, theoretically justified by their non-systematic nature (Pastor et al. 2021). Empirical validation in Section 4.3 rules out material bias.

$k = 1, \ldots, K$ to index the global factors.

Roll and Srivastava (2018)'s mimicking portfolio is a portfolio that minimizes idiosyncratic risk while retaining the same loadings on the global factors for target asset j. In our applications, j will be the index for the collectibles.

The mimicking portfolio is composed of basis assets $i = 1, \ldots, N$. For each basis asset i, we estimate the asset's global factor exposures

$$R_{i,t} = \alpha_i + \beta_{i,1} f_{1,t} + \beta_{i,2} f_{2,t} + \cdots + \beta_{i,K} f_{K,t} + \epsilon_{i,t} \tag{9}$$

Then, the portfolio problem Roll & Srivastava (2018) solve can be formulated as

$$\begin{aligned} \min_{\boldsymbol{\omega}} & \sum_{i=1}^{N} \sum_{m=1}^{N} \omega_i \omega_m \widehat{\sigma}_{i,m} \\ \text{s.t.} \quad & \sum_{i=1}^{N} \omega_i \widehat{\beta}_{i,k} = \widehat{\beta}_{j,k} \quad \forall k \\ & \sum_{i=1}^{N} \omega_i = 1 \end{aligned}$$

where the $\widehat{\beta}_{j,k}$ are estimated from Equation (8) for target asset j, the $\widehat{\beta}_{i,k}$ are estimated from Equation (9) for basis assets $i = 1, \ldots, N$, and $\widehat{\sigma}_{i,m}$ denotes the residual covariance of basis assets i and m from equation (9). In words, the objective is to construct the portfolio of liquid securities with the minimum idiosyncratic risk that matches the factor sensitivities of the target asset. In our application, this is the portfolio of stocks and bonds with the minimum idiosyncratic risk that matches the factor sensitivities of the collectibles portfolio.

Our identification strategy assumes that the factor mimicking portfolio (FMP) spans the financial sources of compensation relevant for collectibles. Any residual return difference is interpreted as emotional yield. While this relies on the completeness of the factor space, we mitigate concerns by using principal components from global equity and bond markets, which explain over 90% of variation.

To be precise, $\widehat{\Sigma} = \text{Cov}(\widehat{\epsilon}_{1,t}, \ldots, \widehat{\epsilon}_{N,t})$ is the $N \times N$ covariance matrix where the $\widehat{\epsilon}_{i,t}$ are the residuals estimated for the basis assets in equation (9). A key assumption Roll and Srivastava (2018) make for purposes of tractability is that the residuals are orthogonal, that is, $\text{Cov}(\widehat{\epsilon}_{it}, \widehat{\epsilon}_{mt}) = \widehat{\sigma}_{i,m} = 0 \ \forall i \neq m$. To avoid assuming residual orthogonality, we solve the portfolio problem numerically.

In addition, depending on the target asset and the set of basis assets, it may be undesirable (or impractical) to ensure that $\sum_{i=1}^{N} \omega_i \widehat{\beta}_{i,k} = \widehat{\beta}_{j,k}\ \forall k$. For example, the cost of satisfying this constraint may be an unreasonably high residual volatility. To account for this trade-off between better matching factor exposures and minimizing the mimicking portfolio's residual volatility, we formalize this trade-off by reframing the optimization problem:

$$\begin{aligned}
\min_{\boldsymbol{\omega}} \ & \sum_{i=1}^{N} \sum_{m=1}^{N} \left(\frac{\omega_i \omega_m \widehat{\sigma}_{i,m}}{\widehat{\sigma}_j^2} \right) + \kappa \left(\sum_{k=1}^{K} \left| \sum_{i=1}^{N} \omega_i \widehat{\beta}_{i,k} - \widehat{\beta}_{j,k} \right| \right) \\
\text{s.t.} \quad & \sum_{i=1}^{N} \omega_i = 1 \\
& \omega_i \geq 0 \ \forall i
\end{aligned}$$

where $\widehat{\sigma}_j^2$ denotes the residual variance of the target asset estimated from equation (8). The first term is the ratio of the mimicking portfolio's residual variance to the target asset's residual variance and the second term is the sum of the absolute differences between the target asset's factor exposures and the mimicking portfolio's factor exposures. κ determines how the investor trades-off reducing the mimicking portfolio's residual variance and better matching the factor exposures of the target asset.

FMP residual variance is materially reduced on average; this supports that systematic exposures are well matched, limiting omitted-factor concerns.

We include a non-negativity constraint for the mimicking portfolio weights for two key reasons. First, this contributes to greater stability in the estimated weights across specifications. Second, this is more broadly implementable for the typical investor (who can't get unlimited leverage), reflecting the spirit of Sharpe's (1992) style analysis.

4.3 Addressing Return Autocorrelation

It is well known that aesthetic assets are infrequently traded, leading to high return autocorrelation, which ultimately leads standard estimators to underestimate the true variance (Andersen et al. 2017) and misestimate the covariance (Scholes & Williams 1977; Dimson 1979). While Campbell (2008) and Dimson & Spaenjers (2011) apply the Geltner (1993) unsmoothing method for art and stamps respectively, we seek to avoid the method's strong assumptions. Instead, we rely on the model-free approach of Dimson's (1979) "aggregated coefficients" for estimating autocorrelation-consistent factor loadings.

Dimson's (1979) autocorrelation-consistent slopes are estimated from the following regression:

$$R_{j,t} = \alpha_j + \sum_{l=0}^{L} \beta_{j,1,l} f_{1,t-l} + \sum_{l=0}^{L} \beta_{j,2,l} f_{2,t-l} + \cdots + \sum_{l=0}^{L} \beta_{j,K,l} f_{K,t-l} + \epsilon_{j,t}$$

where L is the number of statistically significant autocorrelation lags for the dependent variable and a consistent estimate of the slope is obtained as the aggregated coefficients, for example, $\sum_{l=0}^{L} \beta_{j,1,l}$.[10]

To address potential overfitting and to facilitate the relaxation of $T > (L+1)K$ when L gets large, we consider estimating the factor loadings using not only ordinary least squares, but also lasso, ridge, elastic net, and partial least squares (PLS) regression.

We choose to adopt partial least squares (PLS) because it provides stable loadings and minimizes factor-matching error under severe multicollinearity and a small effective sample size. We do not adopt ridge/lasso/EN as primary estimators because their shrinkage objective minimizes prediction error by penalizing coefficient magnitudes, which biases loadings toward zero and can distort the exposure geometry required for factor-mimicking; PLS, by contrast, directly targets covariance with the target series, which is aligned with our factor-matching objective.

Consistent with Nelson & Kim (1993), overlapping multi-period returns induce strong serial correlation and can yield spurious fit in small samples, while switching from annual to monthly data does not materially change the relevant t-ratio distribution because one observes the same nonstationary process more frequently rather than obtaining independent draws. In such small-n, high-ρ settings, formal train/test splits or K-fold cross-validation add limited value for our *explanatory* objective (exposure replication). We therefore prioritize PLS—which directly targets covariance with the target series—and report transparent diagnostics (residual-variance reduction; factor relevance via max $|\beta|$; scaled MAD) and broad specification stability.[11]

[10]Note that lags address dependent variable autocorrelation while leads (which are not included here) address independent variable autocorrelation.

[11]Nelson and Kim (1993) show that (i) overlapping horizons elevate serial correlation and inflate apparent R^2 and t-ratios in small samples; (ii) monthly sampling does not materially alter t-ratio behavior versus annual data, because it does not increase the number of *independent* observations; and (iii) even HAC or HH-type corrections can be too small in finite samples with heavy overlap. These features reduce the informativeness of standard CV splits for exposure-matching tasks. Our diagnostics (residual-variance reduction; factor relevance; scaled MAD) and extensive specification stability are therefore more informative for the *geometry* of factor-matching than CV-style prediction error in this setting.

4.4 Assessing Mimicking Portfolio Performance

We consider several key measures to assess the performance of our mimicking portfolios:

1. **Residual Variance Ratio**: The ratio of the mimicking portfolio's residual variance to the target asset's residual variance: $\sum_{i=1}^{N}\sum_{m=1}^{N}\left(\frac{\omega_i\omega_m\widehat{\sigma}_{i,m}}{\widehat{\sigma}_j^2}\right)$. This ensures that the FMP has less idiosyncratic risk than the test asset. For interpretability, we compare the target asset's residual volatility with the FMP's residual volatility.

2. **Maximum Absolute Loading**: The maximum absolute target asset factor exposure: $\max|\widehat{\beta}_{j,k}|$. This ensures the factors are appropriate for the given test asset. For example, if the collectibles portfolio does not load on any of the pervasive factors, then the factors are not appropriate for the collectible and the FMP is unreliable.

3. **Mean Absolute Deviation (MAD)**: The average absolute difference between the mimicking portfolio's factor exposures and the target asset's factor exposures: $\frac{1}{K}\sum_{k=1}^{K}\left|\sum_{i=1}^{N}\omega_i\widehat{\beta}_{i,k} - \widehat{\beta}_{j,k}\right|$. This is a measure of how well the FMP matches the test asset's factor exposures. To understand how large or small this value is in each specification, we normalize it by: (1) the maximum absolute loading; and (2) the average absolute loading.

4.5 Omitted-factor risk: an analytical bound

Let F denote the K-dimensional factor space spanned by our global stock–bond PCs and let g be any omitted factor orthogonal to F (if it is not orthogonal, its priced component is already in F). With R_C the collectible's return and R_F its financial component, Eq. (7) implies our estimator equals $\mathbb{E}[R_{FMP}] - \mathbb{E}[R_F]$ up to the (positive) cost term. If a priced g exists with price of risk λ_g (the mean of g when $\mathrm{Var}(g) = 1$), then the omitted-factor bias in our estimator is

$$\text{Bias} \;=\; -\,\beta_{C,g}\,\lambda_g,$$

because the FMP, by construction, has zero exposure to g in the orthogonal complement of F. By Cauchy–Schwarz and $\mathrm{Var}(g) = 1$,

$$|\beta_{C,g}| \;=\; \frac{|\,\mathrm{Cov}(R_C - \Pi_F R_C,\; g)|}{\mathrm{Var}(g)} \;\le\; \sigma_{\text{resid}}(R_C),$$

where Π_F is the projection on F and $\sigma_{\text{resid}}(R_C)$ is the collectible's residual volatility from the same regression used to estimate βs. Hence, for any omitted priced factor orthogonal to our PCs, the **absolute** EY bias obeys the simple bound

$$|\text{Bias}| \ \le \ \sigma_{\text{resid}}(R_C) \cdot |\lambda_g|. \tag{10}$$

Proof. Write $R_C = \Pi_F R_C + (R_C - \Pi_F R_C)$, where Π_F projects onto F. Since $g \perp F$, $\text{Cov}(\Pi_F R_C, g) = 0$. Thus $\beta_{C,g} = \text{Cov}(R_C - \Pi_F R_C,\, g)/\,\text{Var}(g)$, and with $\text{Var}(g) = 1$ the Cauchy–Schwarz inequality yields $|\beta_{C,g}| \le \sigma_{\text{resid}}(R_C)$. The EY estimator equals $\mathbb{E}[R_{\text{FMP}}] - \mathbb{E}[R_F]$ up to the (positive) cost term; the FMP has zero exposure to g in the orthogonal complement of F, so the bias is $-\beta_{C,g}\lambda_g$. □

This delivers two implications with quantities we already report. First, since the first ten PCs explain about 90% of variation in global stock–bond returns, any orthogonal factor must live in a low-variance subspace (if it were pervasive and priced, it would appear among the leading PCs). Second, our FMPs materially reduce residual volatility—mean (median) reduction 9.61 (6.80) percentage points—leaving small $\sigma_{\text{resid}}(R_C)$ and thus a small bound in Equation 10.[12] Consequently, under any realistic $|\lambda_g|$ (annual price of risk), the worst-case impact on EY is second order relative to our average estimate ($\sim$ 2.6% p.a.). These diagnostics, together with the stability of EY across six FMP specifications and across currencies/frequencies, indicate that omitted-factor risk is unlikely to overturn our conclusions and, if anything, our reported EY is conservative (downward-biased).

5 Empirical Results

Applying our emotional yield framework to the data, we estimate that collectibles emotional yields are positive and nontrivial in magnitude. Of particular importance, we reach this conclusion even before we consider the various sources of underestimation, many of which are of first-order importance.

[12]See Section 5.1 for more details, as well as Table 4 and Appendix Tables A5 & A6 for series-level residual-volatility reductions.

5.1 Emotional Yield Estimates

Table 4 reports our baseline emotional yield estimates for the 30 collectibles price indices. We estimate emotional yields using six factor mimicking portfolio specifications that vary in principal component span and basis asset composition. Full results and diagnostics are reported in the Online Appendix.[13] The reported results are from the combination of factors and basis assets that yields the best performance in terms of residual volatility reduction, factor relevance, and factor matching. Importantly, we choose the best performing specification without regard for the emotional yield estimate. The Online Appendix reports the results from all 6 specifications for each collectible return series. The emotional yield estimates are generally quite stable across specifications, and the qualitative conclusions are unchanged when using other reasonable choices.

24 of the 30 collectibles price indices have positive emotional yield point estimates, although only 14 of the 24 are statistically significantly positive at the 5% significance level. The limited statistical significance is due to relatively large autocorrelation-adjusted standard errors for the emotional yield time series, which inherits the autocorrelation of the original collectibles return series. Nevertheless, given various forms of underestimation, it's surprising to see the *unadjusted* emotional yields so strongly priced in equilibrium. Focusing only on the annual and quarterly series,[14] the mean and median annualized emotional yield estimates are 2.64% and 2.53%.

Figures 3 & 4 plot the time series of the estimated emotional yields. Figure 3 shows the emotional yield of Public collectibles is lower than that of Specialist collectibles, which is consistent with the message from Figure 1 where the financial returns of Public collectibles are higher than that of Specialist collectibles. Figure 4 also supports the same message. Although the two figures support our argument, these are only of limited direct interest since we focus on estimating unconditional emotional yields instead of conditional emotional yields.

In addition, the factor mimicking portfolios achieve a substantive reduction in residual volatility relative to the collectibles themselves. Two key observations come from our examination of these cross-sectional emotional yield estimates. First, Private collectibles carry the largest emotional yields by an order of magnitude. In the Q1 1998 - Q3 2018 data, the

[13] If bonds and stocks are used for the PCs, we don't consider using only stocks for the basis assets.

[14] This avoids double-counting the monthly series, as they are also converted to quarterly series.

average is 9.55%, much larger than the 2.28% of Public collectibles or the 0.45% of Specialist collectibles. Second, despite great heterogeneity in the underlying baskets, our estimates for the emotional yields of Specialist and Public collectibles are remarkably similar across these two very different time horizons (ie: 1901-2007 and 1998-2018).

Our dataset necessarily tilts toward blue-chip segments with long, reliable time series. We therefore caution that our headline average (about 2.6% p.a.) pertains to the upper tier of collectibles markets; the magnitude may differ in broader segments. That said, the cross-category evidence is informative: Private-domain collectibles (e.g., furniture, rugs) carry larger emotional yields than Public-domain fine art, consistent with stronger private enjoyment and limited signaling scope. This suggests that non-pecuniary dividends are not confined to elite assets, although we refrain from extrapolating to the full mass market in the absence of equally long time series. (See Table 4 and grouped portfolios in the Appendix.)

5.2 Sources of Emotional Yield Underestimation

There are four main sources of emotional yield underestimation: (1) we treat investors as risk-neutral and so ignore the benefits of large reductions in uncompensated risk; (2) no annualized transaction cost is added; (3) repeat-sales price indices suffer from selection bias; and (4) we ignore the liquidity benefits of the FMP relative to the collectibles.

First, we ignore the much lower residual volatility of the FMP, which would make the FMP more attractive than the collectible for a risk-averse investor. In our framework, the FMP is constructed to reduce the portfolio's residual volatility as much as possible while still matching the test asset's factor exposures. This objective function, which does not seek to maximize the portfolio's expected return, implies that the investor is risk-averse. However, in comparing the test asset with the FMP, we focus only on the difference in average returns, and ignore the fact that the FMP reduces the residual volatility by between 2 and 30 percentage points, which would accrue utility benefits to a risk-averse investor. As a result, we underestimate the incremental attractiveness of the FMP's financial return relative to the test asset's financial return, meaning we underestimate the emotional yield.

Under mean–variance preferences, the certainty-equivalent (CE) return increment satisfies

$$\Delta_{\text{CE}} \;=\; \tfrac{1}{2}\,\gamma\left(\sigma^2_{\text{resid},C} \;-\; \sigma^2_{\text{resid},FMP}\right).$$

Because we report only the *reduction in the standard deviation* $\Delta\sigma = \sigma_{\text{resid},C} - \sigma_{\text{resid},FMP}$, a conservative bound is

$$\Delta_{\text{CE}} \ \geq \ \tfrac{1}{2}\,\gamma\,(\Delta\sigma)^2\,,$$

since $\sigma_{\text{resid},C} \geq \Delta\sigma$. Plugging the *median* reduction $\Delta\sigma = 0.068$ (6.8 p.p.): $\Delta_{\text{CE}} \geq 0.46\%$ (CRRA $\gamma = 2$); $\geq 0.93\%$ ($\gamma = 4$); $\geq 1.39\%$ ($\gamma = 6$). Using the *mean* reduction $\Delta\sigma = 0.0961$ yields $\Delta_{\text{CE}} \geq 0.92\%$ ($\gamma = 2$); $\geq 1.85\%$ ($\gamma = 4$); $\geq 2.77\%$ ($\gamma = 6$). These are *lower bounds* because we do not observe $\sigma_{\text{resid},C}$ directly in every series.

Second, we do not add the annualized transaction cost, a positive term, to our estimate of the emotional yield. Our motivating formula for the estimation of the unconditional emotional return is:

$$\underbrace{\mathbb{E}[R_t^E]}_{\text{Emotional Return}} = \underbrace{\mathbb{E}[R_t^{FMP}]}_{\text{FMP Return}} - \underbrace{\mathbb{E}[R_t^F]}_{\text{Collectible's Financial Return}} + \underbrace{\mathbb{E}[R_t^T]}_{\text{Transaction/Holding Costs (Annualized \%)}}$$

We do not try to account for transaction & holding costs because of substantial time variation within and across assets and difficulty in obtaining high quality estimates. For example, Dimson, Rousseau, & Spaenjers (2015) estimate wine storage & insurance costs at between 0.13% and 0.94% for each decade between 1940 and 2000, with the cost of insurance being a fixed fee (eg: 1.6 shilling or 0.075 GBP in March 1940) that is converted into a percent based on average prices during that time period. In contrast, custody costs for stamps are so low that they can be reasonably ignored (Dimson & Spaenjers 2011).

Transaction costs are also complicated, with auction house transaction costs being composed of a buyer's premium and a seller's commission. The buyer's premium, introduced during the mid-1970s, was initially flat at 10% of the hammer price and is currently as high as 25% for hammer prices below $200,000 (Kraussl & Nasser Edinne 2018). While the seller's commission is often estimated at 10% of the hammer price, it is not observed and is negotiable. Many papers assume that roundtrip transaction costs are 20-30% of the hammer price.[15] The annualized transaction cost then depends on the average holding period, often believed to be between 28 years (Mei & Moses 2002) and 40 years (Reitlinger 1961), which

[15] Penasse & Renneboog (2022) argue that total transaction costs are minimally 20% of the sales price while Campbell (2008) notes that total transaction costs can be as much as 30%. Kraussl & Nasser Eddine (2018) document the evolution of the buyer's premium over time, which, when paired with the seller's commission, also gives estimates in this range. Dimson & Spaenjers (2011) use 25% for stamps, which they find is similar for either a round-trip trade through an auction or a dealer (Stanley Gibbons).

would yield an average annualized transaction cost of 0.5-1.1%, at least for recent years.

Third, we do not directly account for the upward-bias of our repeat-sales price indices. Repeat-sales price indices are upward-biased because collectibles do not randomly trade at least twice. Korteweg, Kraussl, & Verwijmeren (2016) show that this selection bias leads a 1960-2013 repeat-sales painting price index to overstate average annual returns by 2.4%. As our repeat-sales price indices may overstate the collectible's average financial return, this is another source of emotional yield underestimation.

Next, we do not attempt to account for the liquidity mismatch between the collectibles and the FMP, which makes the FMP more attractive (all else equal). There is a large body of evidence documenting a positive relation between expected illiquidity and expected returns (eg: Amihud & Mendelson 1986; Amihud 2002; Pastor & Stambaugh 2003; and Dimson & Hanke 2004). Collectibles are illiquid, evidenced by the high transaction costs and long average holding periods. While there are no studies estimating the illiquidity premium in collectibles markets, studies of the US stock market have estimated the annual illiquidity premium to be between 1.7% and 7.5%.[16] By comparing the financial return of the relatively-illiquid collectibles to the financial return of the relatively-liquid factor mimicking portfolio, we fail to adjust for return differences based on liquidity. As a result, we overestimate the collectible's financial return and thus underestimate the emotional yield.

Lastly, the prospect theory (Kahneman & Tversky, 1979) implies that downside states receive extra weight $\lambda > 1$ relative to gains. If downturns occur with probability p_d and emotional shocks have return-equivalent dispersion σ_e (Lovo & Spaenjers, 2018), the certainty-equivalent increment from the FMP's downside-risk mitigation satisfies

$$\Delta_{\text{LA}} \approx (\lambda - 1)\, p_d\, \kappa\, \sigma_e,$$

where $\kappa \in [0, 1]$ captures the share of residual downside risk eliminated by the FMP. Using $\lambda = 2.25$, $p_d = 0.15$, $\sigma_e = 3\%$, and $\kappa = 1$ gives $\Delta_{\text{LA}} \approx 0.56\%$ p.a.; values near 1% arise under modestly higher p_d or σ_e. This term enters positively in our bias-adjusted estimator:

$$\text{EY}^{\star} = \text{EY} + \tau + L + b_{\text{RS}} + \Delta_{\text{CE}} + \Delta_{\text{LA}}. \tag{11}$$

[16] Pastor & Stambaugh (2003) estimate a 7.5% annual premium, Acharya & Pedersen (2005) estimate a 4.6% annual premium, and Hagstromer, Hansson, & Nilsson (2013) estimate a 1.7-2.1% annual premium.

See Table A19 for the sensitivity of Δ_{LA} to each parameter.

5.2.1 Lower-bound magnitudes (back-of-the-envelope)

Equation (11) implies that the omitted components——transaction/holding costs (τ), liquidity advantages of the FMP (L), biases in repeat-sales price indices (b_{RS}), risk-aversion benefits from lower resiudal volatility (Δ_{CE}), and downside mitigation benefits (Δ_{LA})-—enter with a positive sign. Prior evidence suggests these can be economically meaningful. (i) Transaction costs: round-trip costs $\sim$ 20˘30% (auction premiums + seller commissions) and average holding periods of 28–40 years imply annualized 0.5–1.1%, which adds directly to emotional yield. (ii) Liquidity premia on illiquid assets are typically 1.7–7.5% p.a., which the FMP largely avoids; not recognizing this understates the FMP's attractiveness and thus understates emotional yield. (iii) Repeat-sales selection bias in art indices is $\sim$ 2.4% p.a. upward, which overstates collectible financial returns and raises the implied emotional yield. (iv) The FMP reduces residual volatility by $\sim$ 7˘10 pp on average; a risk-averse investor would ascribe additional utility to this reduction, further increasing the implied emotional yield, with plausible certainty-equivalent increments of 0.5% to 2.8% p.a. (v) We ballpark additional downside-risk mitigation at roughly 1%.

Finally, Lemma 10 implies that even a worst-case omitted factor orthogonal to our PCs cannot raise the collectible's expected financial return by more than $\sigma_{\text{resid}}(R_C) \cdot |\lambda_g|$; given our residual-volatility diagnostics and plausible prices of risk, this bound is small. For example, with residual volatility of 10%, an annual risk premia of 10% (large relative to known factors) would still only pose a 1.0% downward revision.

Together, these adjustments imply that our reported average $\approx$ 2.6% is a conservative lower bound. Our underestimates, which sum to 6.1-14.8%, substantially outweigh any potential overestimates from omitted risk factors, which reach 1.0% only under aggressive assumptions.

5.3 Limitations and Generalizability

Our dataset focuses on blue-chip segments (Table 1) because these are the only categories with sufficiently long and reliable time series. We acknowledge this limitation and clarify that our headline estimate (2.64%) pertains to the upper tier of collectibles markets. Emotional dividends likely exist across all quality segments, but their magnitude may differ. For example, family heirlooms or low-value collectibles could exhibit even higher emotional yields (potentially substantial in percentage terms).

Our analysis already includes some heterogeneity, as we study 13 categories spanning public-domain (e.g., fine art), specialist-domain (e.g., coins, wine), and private-domain (e.g., furniture, rugs). The cross-category evidence shows that Private-domain items (e.g., furniture, rugs) carry larger EYs than Public-domain fine art—about 9.5% vs. 2.3% in the quarterly data. These patterns align with intuition: items valued primarily for personal enjoyment rather than public prestige carry the largest non-pecuniary returns.

Figure 5 illustrates rental yields for mid-tier artworks, which typically range from 6-30% on an annualized basis. The table collates advertised annualized rental yields (as a percent of fair market value) for "middle-of-the-pack" artworks available via corporate or short-term rental programs. These monetized display rights typically sit between two anchors: (i) our blue-chip estimates, where emotional value is significant but not directly paid out in cash; and (ii) family-heirloom/private cases, where the intrinsic attachment can be "priceless." The rental yields vary by artwork tier, term, insurance/logistics bundle, and provider, but they consistently indicate positive, economically meaningful payments for display utility, reinforcing that non-pecuniary dividends are not confined to elite assets. We include the figure only as a point of reference. In the Appendix, we discuss how rental yields relate conceptually (but not identically) to emotional yields from direct ownership.

5.4 Speculative vs. collector interest

The cross-sectional ordering– Private > Public > Specialist– is consistent with collector-driven segments exhibiting larger EYs than segments plausibly more exposed to speculative flows. We also mark commonly discussed speculative episodes (e.g., late-1970s) in Appendix Fig. A8 and note that some Public-domain series exhibit visible movements, though we refrain from causal claims absent clean proxies for speculation vs. collector demand.

5.5 Co-movement with macro and social factors

To complement Table 4 and get a sense how EY comoves with the economy, we provide a compact correlation analysis of the EY composites with three non-priced factors suggested by the editors: (i) inflation (CPI inflation); (ii) war/political instability (WWI/WWII dummies as portability shocks); and (iii) wealth concentration (top income share). The pairwise correlations are modest, and short panels relating EYs to these proxies yield small, unstable coefficients (Appendix Tables A11 to A13 and A17; Figs. A7 to A10). Visually, the late-1970s show movements in some series, but the cross-category pattern is not systematic once the FMP removes traded risk, which is consistent with our unconditional interpretation. We leave deeper, conditional modeling to future work.

5.6 Emotional yields across collectibles

Emotional yields (EY) are positive on average and move together across categories. A cross-asset EY correlation matrix[17] shows very high within-series/variant correlations (e.g., alternative constructions of Stamps, Art, Wine) and moderate cross-category correlations, indicating a common EY component beyond idiosyncratic series choices. EY is economically and statistically distinct from the financial component captured by $\beta \cdot PC$, as shown by large reductions in residual volatility when we fit $\beta \cdot PC$ and the stability of the residual EY over time (Appendix Table A11).

5.7 Event-Time Behavior of Emotional Yields

While Section 5.5 provides a descriptive view of unconditional co-movement between emotional yields (EY) and broad macro/social proxies—primarily through simple correlations—this section goes further by introducing a conditional and event-driven perspective. Specifically, Section 5.7.1 uses asset-level regressions to identify systematic sensitivities of EY to macroeconomic and speculative factors, revealing sign patterns that vary across eras (e.g., negative loadings on wealth concentration and war risk, inflation sensitivity post-1982). This moves beyond mere correlation by testing whether EY responds predictably to state variables once traded risk is stripped out.

5.7.1 Macro sensitivity

Asset-level regressions (Table A13) relate EY to macro and speculative proxies. EY loads negatively on wealth concentration and war/political risk for several assets; recession share is weak over the full sample but becomes more positive post-1982; one-year expected inflation is typically negative post-1982; and volume growth is not robustly significant. These patterns

[17] Due to limited space, we do not report the result here but it is available upon request.

are consistent with EY rising in inflationary/panic episodes (non-financial demand pressures) and weakening in deflationary collapses.

5.7.2 Event-time EY around major shocks.

In ±10-year windows around 1914, 1930, 1973, and 2008, cross-collectible EY spikes at inflationary/financial stress events and falls in deflationary collapse (Figure A8 to A10). Relative to the pre-event baseline (average EY over $k = -10, \ldots, -1$), the event-year jump is $\approx +11.9$ pp for 1973 (peak within ±2 years $\approx +15.5$ pp) and $\approx +9.8$ pp for 2008 (peak $\approx +14.9$ pp). Around the Great Depression, EY turns strongly negative (post $0, \ldots, +2$ minus pre $-3, \ldots, -1 \approx -12.2$ pp; trough ≈ -26.3 pp). WWI (1914) shows a small event-year uptick ($\approx +3.8$ pp) with high volatility and quick reversal. These effects remain with balanced-panel and median aggregation, and—where sample length allows—are visible using rolling-origin out-of-sample $\beta \cdot PC$ EY for 1973 and 2008 (Figure A9).

5.8 Subsample stability

Re-estimating within four historical splits (pre/post WWII, 1973, 1982, 1990) yields broadly similar magnitudes once HAC uncertainty is accounted for: in 89–100% of asset×breakpoint cases, the Post–Pre change in mean EY lies within pooled HAC SEs, with median $|\Delta| \sim$ 1.1–1.4,pp. Median refit R^2 is comparable across splits (e.g., pre/post-1973: 0.32→0.31; pre/post-1990: 0.29→0.31), indicating that the $\beta\cdot$ PC mapping is not confined to one era. Sensitivity regressions show modest, mixed links: war/political-risk loads negatively most often; recession share tends to be positive pre-1990; wealth concentration is rarely significant and negative when it is; expected inflation (post-1982) is weakly negative. For evidence, see Figure A8 and Table A11.

5.9 Block-bootstrap inference.

To complement HAC standard errors, we compute moving-block bootstrap (MBB) confidence intervals for the mean annual emotional yield (EY). MBB preserves serial dependence without imposing parametric assumptions, which is important given autocorrelation in annual series. For each series with $T \geq 40$ annual observations, we resample overlapping blocks of length $L \in \{5, 10\}$ (roughly one–two business-cycle horizons) and generate

$B = 2{,}000$ bootstrap replications of the mean. We report bootstrap standard errors and 95% percentile confidence intervals (Table A16). Results are close to HAC estimates and stable across block lengths, reinforcing that inference on mean EY is not an artifact of small-sample dependence.

5.10 Speculative episodes

We provide a concise event-time summary of emotional yields (EY) around major speculative or stress episodes: World War I (1914), the Great Depression (1930), the 1973 inflation/oil shock, and the 2008 financial crisis (see Appendix Table A17 and Figure A8). For each event, we report:

- the *event-year jump*, defined as

$$\Delta_{k=0} - \overline{\text{pre}}, \quad \text{where pre} = \{k = -3, -2, -1\},$$

- and the *short-horizon post–pre difference*, defined as

$$\overline{k \in \{0, 1, 2\}} - \overline{k \in \{-3, -2, -1\}}.$$

These statistics are computed on the *cross-collectible average EY* after removing traded risk via the factor-mimicking portfolio (FMP). The patterns are descriptive and suggest *state-dependent non-pecuniary demand pressures*, but we refrain from making structural or causal claims. Figure A9 illustrates out-of-sample emotional yield (EY) dynamics around two major stress episodes: the 1973 oil/inflation shock and the 2008 financial crisis. EY rises sharply in both cases, peaking at approximately +15 percentage points within two years post-event for 1973 and +14 percentage points for 2008. These spikes suggest that emotional dividends intensify during periods of macro stress, consistent with state-dependent non-pecuniary demand. Confidence intervals widen near the event, reflecting estimation uncertainty. This evidence complements our unconditional estimates and reinforces the lower-bound interpretation of reported EY.

5.11 Estimator transparency (PLS and short-sample discipline).

Given our short effective sample and data constraints, we do not add ridge/lasso/elastic-net comparisons to avoid overfitting and spurious precision. We retain PLS because it targets covariance with the target series and is robust in short-T designs. We document exact preprocessing (standardization, Dimson lags, factor set), the blocked 10-fold CV rule for component selection, and a within-PLS sensitivity (components = 1–3). Results and code are provided for full reproducibility from the authors upon request.

Table A18 is included to provide transparency on emotional yield behavior across individual collectible series under the PLS-only framework. Given the short sample and overfitting concerns, we omit shrinkage-based comparators and instead report descriptive EY statistics to clarify model discipline. This complements our response letter and supports the decision to retain PLS as the sole estimator, consistent with the short-T rationale.

6 Further Robustness

The Appendix includes a variety of robustness tests, where we consider rebasing in an unselected currency or use a different time horizon, all of which do not qualitatively change our results. Here, we discuss some of the more nuanced robustness tests.

6.1 Transaction-cost sensitivity (back-of-the-envelope) and estimator robustness.

Our findings remain robust across reasonable variations in transaction cost assumptions (0.5–1.3% p.a.) and estimator settings (e.g., cross-validation folds, component limits, and predictor scaling), with emotional yield estimates showing minimal sensitivity to these changes See Table A8 and Table A14.

6.2 Rolling-origin OOS diagnostic

To ensure our estimator is not overfit, we implement a rolling-origin out-of-sample (OOS) check. Starting with an initial window of at least 30 annual observations, we re-estimate factor loadings each year using partial least squares (PLS) with blocked cross-validation for component selection. For each subsequent year, we predict the collectible's financial component and compute the residual as the emotional yield (EY). We report OOS R^2, correlation between actual returns and predicted financial component, and summary statistics for EY residuals (mean, standard deviation, and share > 0). Table A14 shows that OOS R^2 values are slightly negative—expected given our explanatory objective—but correlations remain meaningful (0.27–0.45 for art and stamps), and EY residuals are centered near zero with dispersion typical of annual series. These diagnostics confirm that our unconditional EY estimates are not artifacts of in-sample fit and that the PLS estimator remains parsimonious (avg. 1–2 components).

7 Conclusion

We design a method for estimating emotional yields of collectibles and apply it to 30 collectibles return series spanning 13 distinct asset classes. The intuition behind our strategy is simple: investors choose between a well-diversified collectibles portfolio and a factor mimicking portfolio by comparing the expected returns, both financial and non-financial. The emotional yield is the difference in expected financial returns, which makes the investor indifferent between owning the collectibles and the factor mimicking portfolio.

We find that most collectibles carry a moderate and positive emotional yield on the order of 2.5% annually. This value can be viewed as a lower bound because of several simplifications that lead us to underestimate the emotional yield. We find that emotional yields appear fairly stable across different time periods, and that private-domain collectibles carry much larger emotional yields than public-domain or specialist-domain collectibles.

Our finding that emotional yields, or emotional dividends, are priced in equilibrium sheds light on the future of ESG investing. As theoretically predicted in Pastor, Stambaugh, & Taylor (2021), our results suggest that ESG investing, in equilibrium, will feature nontrivial non-pecuniary benefits and so lower financial returns.

Our results also have practical implications for a growing base of retail investors who are drawn to alternative assets (whether collectibles or non-fungible tokens). These emotional or aesthetic assets may underperform comparable portfolios of stocks and bonds, lending credit to the old adage that collectors should "buy what they love" and not buy aesthetic assets purely as financial investments.

Work on estimating emotional dividends, or non-pecuniary returns, is still in its infancy. Extending our framework to other long-term asset classes like luxury residential real estate could prove fruitful. One benefit of real estate is that close alternatives are more easily identifiable, and comparing the cost of renting and buying the same property (or similar properties of heterogeneous quality) may provide a means of constructing more precise estimates of emotional yields.

Our estimates show that emotional dividends are priced in equilibrium: investors accept meaningfully lower financial returns than a liquid, factor-matched alternative to obtain non-pecuniary benefits from collectibles. This mechanism is directly relevant in today's financialized market—where fractionalization and art-backed lending separate financial exposure from consumption/display—and it provides a disciplined analogy for contexts like ESG, without making claims about ESG returns per se. We document limited co-movement with a few non-priced factors and the expected cross-sectional ordering across domains; exploring predictability and state dependence (e.g., speculation vs. collecting) is a promising avenue for future research. Future work could examine settings where display or rental rights are explicitly monetized and test whether such rights reduce the estimated emotional yield.

Figures

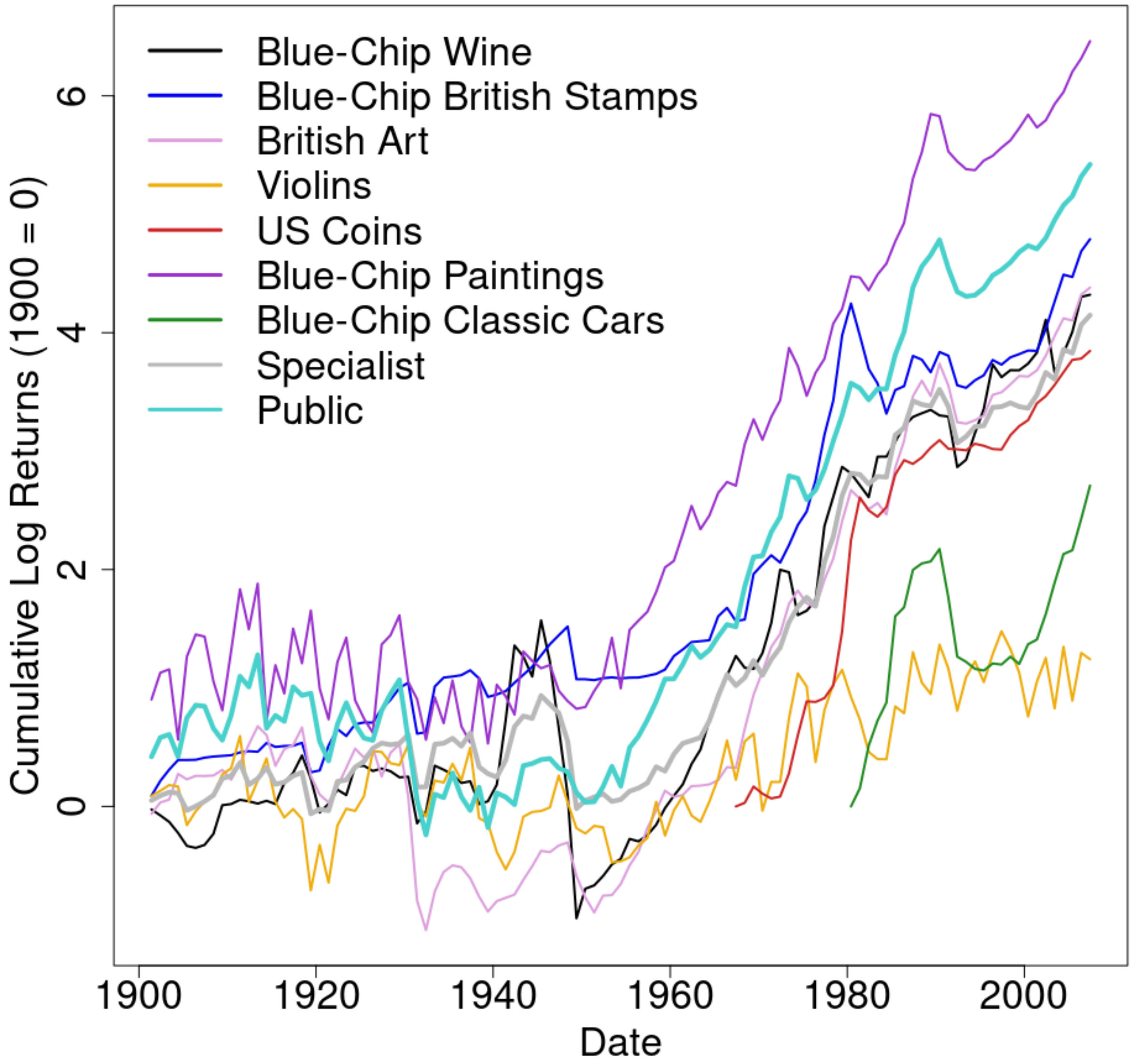

Figure 1: Cumulative Log Returns for Annual USD Series

This figure plots the cumulative log returns of the annual USD collectibles over the 1900-2007 time period. 1900 is scaled to have a cumulative log return of 0, although US coins and blue-chip classic cars are scaled to 0 for the first year of the series (in 1967 and 1980, respectively). The Specialist and Public series are cumulative equal-weighted averages of the non-missing log returns for groups of similar collectibles. Specialist-domain collectibles include blue-chip wine, blue-chip British stamps, violins, US coins, and blue-chip classic cars. Public-domain collectibles include British art and blue-chip paintings.

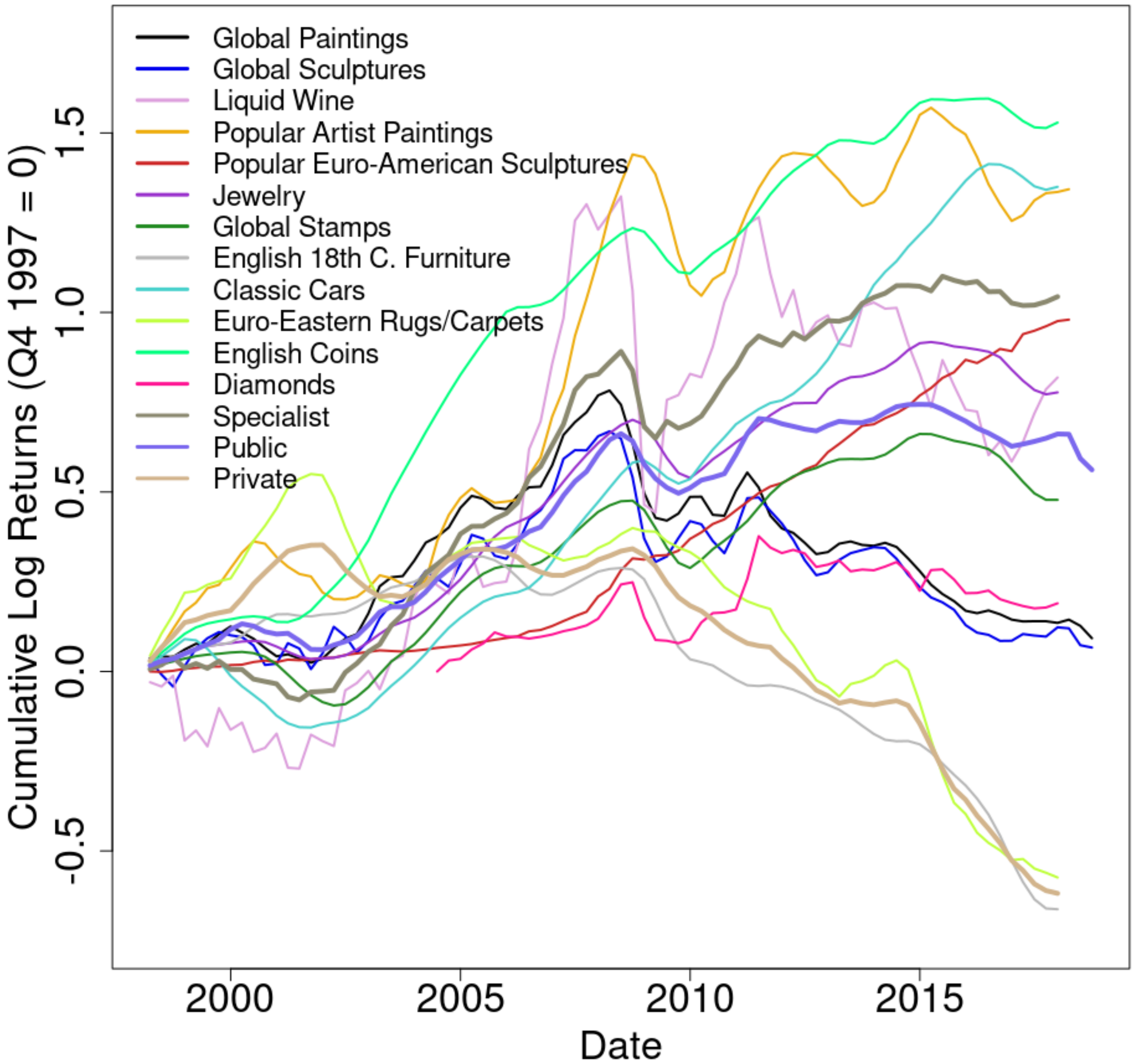

Figure 2: Cumulative Log Returns for Representative Quarterly USD Series

This figure plots the cumulative log returns of the quarterly USD collectibles over the Q1 1998 - Q3 2018 time period. Q4 1997 is scaled to have a cumulative log return of 0, although diamonds are scaled to 0 for the first quarter of the series (Q2 2004). The Specialist, Public, and Private series are cumulative equal-weighted averages of the non-missing log returns for groups of similar collectibles. Specialist-domain collectibles include liquid wine, global stamps, classic cars, and English coins. Public-domain collectibles include global paintings, global sculptures, global photographs, global drawings, global prints, popular artist paintings, popular artist European & North American sculptures, jewelry, and diamonds. Private-domain collectibles include English 18th century furniture and European & Eastern Rugs & Carpets.

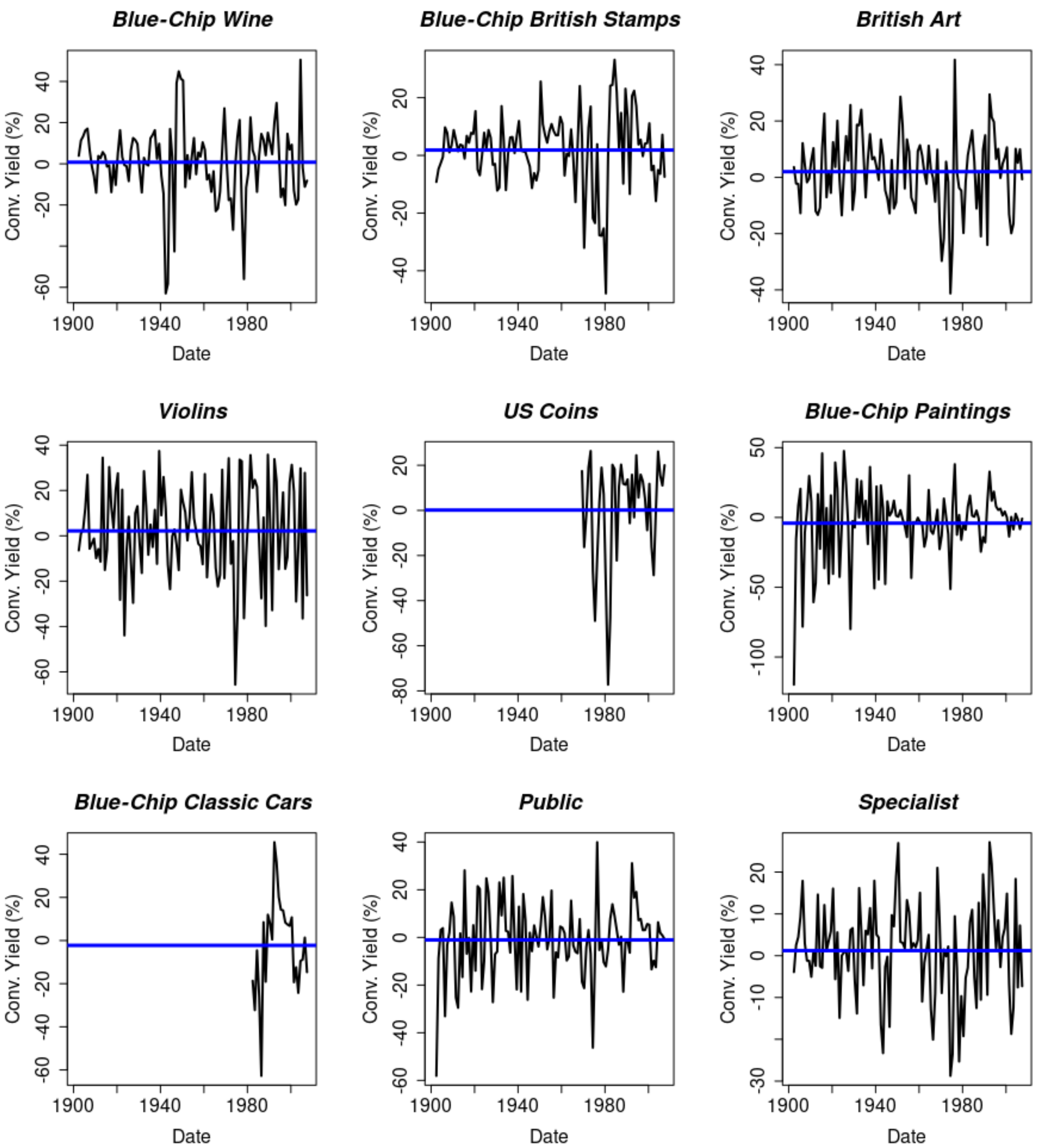

Figure 3: Exponentially-Smoothed Emotional Yields for Annual USD Returns

This figure plots the exponentially-smoothed emotional yields of the annual USD collectibles over the 1900-2007 time period. The exponential smoothing function takes the form $s_t = \alpha x_t + (1 - \alpha)s_{t-1}$, where x_t is the estimated emotional yield for period t. We set $\alpha = 0.2$ to allow for a moderate degree of smoothing. The Specialist and Public series are equal-weighted averages of the non-missing emotional yields for groups of similar collectibles. Specialist-domain collectibles include blue-chip wine, blue-chip British stamps, violins, US coins, and blue-chip classic cars. Public-domain collectibles include British art and blue-chip paintings.

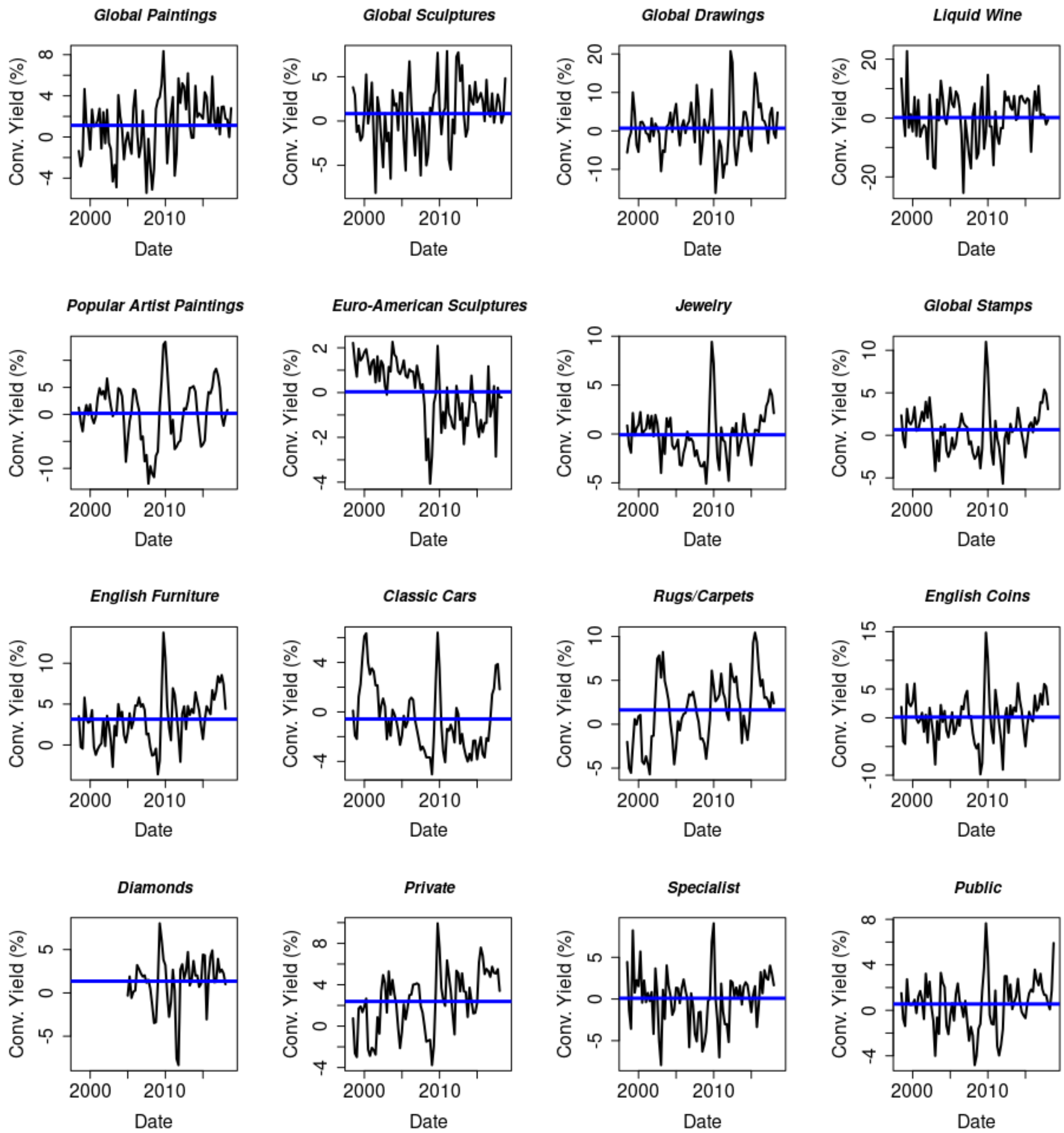

Figure 4: Exponentially-Smoothed Emotional Yields for Representative Quarterly USD Returns

This figure plots the exponentially-smoothed emotional yields of the quarterly USD collectibles over the Q1 1998 - Q3 2018 time period. The exponential smoothing function takes the form $s_t = \alpha x_t + (1-\alpha)s_{t-1}$, where x_t is the estimated emotional yield for period t. We set $\alpha = 0.2$ to allow for a moderate degree of smoothing. The Specialist, Public, and Private series are equal-weighted averages of the non-missing emotional yields for groups of similar collectibles. Specialist-domain collectibles include liquid wine, global stamps, classic cars, and English coins. Public-domain collectibles include global paintings, global sculptures, global photographs, global drawings, global prints, popular artist paintings, popular artist European & North American sculptures, jewelry, and diamonds. Private-domain collectibles include English 18th century furniture and European & Eastern Rugs & Carpets.

Table 11: Art Rental Yields

This table presents the range of annualized rental yields charged by an assortment of firms that offer art rentals. The first column lists the names of the companies. The second column presents the range of annualized rental yields charged by these firms. The third column reports the range of quoted rental yields available on each company's website. When quoted in dollar values, I obtain rental yields by dividing the rental fee by the listed sales price. Note that, while most of the rental yields are monthly, some firms require a minimum number of months for the rental. The last column is the maximum sales price for any artwork that is listed for rent. Since the rental yields tend to decrease as the listed sales price increases, the maximum sales price is associated with the lowest rental yield.

Company	Annualized Rental Yield	Quoted Rental Yield	Maximum Price for Rented Art
Artemus	-	-	$100 M (luxury art in New York)
Art-Lease	6-8%	6-8% annually	Luxury art in Hong Kong
Ryan James Fine Arts	6-42%	0.5-3.5% per month	$7,000
Get Art Up	12-300%	1-25% per month	$4,000
Northwest Museum	16-72%	4-18% for 3 months	$3,800
Artolease	18-54%	1.5-4.5% per month	-
Teichert Gallery	24-120%	2-10% per month	$10,000
Agora Gallery	36%	3% per month for 3+ months	Minimum value of $20,000
Artforte	36-42%	3-3.5% per month	-
Artspay	48%	4% per month for 4-6 months	-
Hang Art	52-120%	13-30% for 3 months	$50,000
Riverfront Art Gallery	72-144%	6-12% per month	-
Rise Art	84-240%	7-20% per month	$16,000

Figure 5: Illustrative rental-yield table (excerpt from Vorsatz) showing annualized rental yields for "middle-of-the-pack" artworks. This figure highlights how monetized emotion yields for rental markets can be compared to our estimates for blue-chip collectibles.

Tables

Table 1: Details of Collectibles Price Indices

This table provides brief descriptions of the collectibles price indices. Panel A describes the longer-term (annual) raw series. Panel B describes the more recent (quarterly and monthly) raw series.

Index Name	Data Description
	Panel A. Longer Term
British Art	This annual repeat-sales price index spans 1766-2007 and is denominated in GBP. The index focuses on British paintings and drawings and is provided by Goetzmann, Renneboog, & Spaenjers (2011). The index is based on 1,336 repeated sales found by merging the Reitlinger (1961) and Renneboog & Spaenjers (2013) datasets.
Blue-Chip Paintings	This annual repeat-sales price index spans 1901-2016 and is denominated in USD. The index focuses exclusively on paintings sold by Sotheby's or Christies post-1950, with prior public transactions included whenever possible using the provenance. The index is provided by Sotheby's and is an expansion of the original 4,896 price pairs of Mei & Moses (2002) to over 80,000 repeat sales in its current form.
Blue-Chip British Stamps	This annual repeat-sales price index spans 1900-2008 and is denominated in GBP. The index begins with the 50 most valuable British stamps in the Stanley Gibbons catalogue in 1900 and adds the missing members of the top 50 most valuable stamps every 9 years, with the basket growing to 127 stamps by the end of the sample. This index is provided by Dimson & Spaenjers (2011).
Blue-Chip Wine	This annual repeat-sales price index spans 1900-2012 and is denominated in GBP. The index focuses on five red Bordeaux wines (the Premier Crus: Haut-Brion, Lafite-Rothschild, Latour, Margaux, and Mouton-Rothschild) and is provided by Dimson, Rousseau, & Spaenjers (2015).
Violins	This annual repeat-sales price index spans 1876-2012 and is denominated in GBP. The index focuses on 320 distinct violins and 1,328 repeat sales and is provided by Graddy & Margolis (2013).

US Coins	This annual repeat-sales price index spans 1968-2012 and is denominated in USD. The index focuses on US coins (pennies, nickels, dimes, quarters, half dollars, and dollars) and is provided by Maslar, Obaid, & Pukthuanthong (2020).
Blue-Chip Classic Cars	This annual capitalization-weighted price index spans 1980-2017 and is denominated in GBP. The index focuses on high-end cars, with the 50 models that are current index constituent having a minimum price of £100,000 and maximum number of survivors at 1,000 units. The index is provided by Historic Automobile Group Inc (HAGI).
Panel B. More Recent	
Global Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all Fine Art auction results (paintings, sculptures, drawings, photographs, prints, watercolors, etc.) recorded by Artprice.com except for antiques and furniture, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
US Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to US auction sales.
Global Paintings	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to paintings.
Popular Artist Paintings*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - March 2018 and is denominated in USD. The index focuses on paintings (Old Masters, European Impressionists, Modern, and Contemporary) by 100 well-known artists including Basquiat and Canaletto, with public auction data sourced globally accounting for 90% of painting sales by value. The index is provided by Art Market Research.
Average Artist Paintings*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - March 2018 and is denominated in USD. The index measures the average value of paintings sold by the average artist in each month and is provided by Art Market Research.

Global Prints	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to prints.
Global Photographs	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to photographs.
Global Drawings	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to drawings.
Global Sculptures	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to sculptures.
Popular Artist European & North American Sculptures*	This monthly exponentially-smoothed moving average sales price index spans January 1985 - March 2018 and is denominated in USD. The index focuses on European & North American sculptures by 100 well-known artists, covering 55,527 works. The index is provided by Art Market Research.
Liquid Wine	This monthly value-weighted price index spans January 1988 - December 2017 and is denominated in GBP. The index focuses on Bordeaux red wines from 24 leading chateaux, and the 100 highest-rated wines (in terms of Robert Parker Jr. scores) trading on the Liv-ex exchange are included in the scarcity-weighted basket. The index is provided by Liv-ex.
Global Stamps*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - December 2017 and is denominated in USD. The index focuses on 25 distinct genres of stamps spanning more than 11 countries. The index is provided by Art Market Research.
English Coins*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - December 2017 and is denominated in USD. The index focuses on hammered & milled English gold & silver coins. The index is provided by Art Market Research.

Classic Cars*	This monthly exponentially-smoothed moving average sales price index spans January 1981 - December 2017 and is denominated in USD. The index focuses on 15 brands of luxury classic cars. The index is provided by Art Market Research.
Jewelry*	This monthly exponentially-smoothed moving average sales price index spans January 1986 - December 2017 and is denominated in USD. The index focuses on four broad genres of jewelry and is provided by Art Market Research.
General Diamonds	This daily value-weighted price index spans January 1, 2004 to January 31, 2018 and is denominated in USD. The index focuses on 300 stone profiles that accounted for approximately 43% of the total market in dollar value at the time of the index composition. The index is provided by IDEX.
European & Eastern Rugs & Carpets*	This monthly exponentially-smoothed moving average sales price index spans January 1985 - December 2017 and is denominated in USD. The index focuses on European and Eastern Rugs & Carpets and is provided by Art Market Research.
English 18th Century Furniture*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - December 2017 and is denominated in USD. The index focuses on 36 genres of English 18th Century furniture and is provided by Art Market Research.
Global Old Masters Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to Old Masters Art.
Global 19th Century Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to 19th Century Art.
Global Modern Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to Modern Art.
Global Post-War Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to Post-War Art.
Global Contemporary Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index uses the same underlying sample as the Global Art index, but restricts consideration to Contemporary Art.

* In constructing the index, Art Market Research includes only the central 80% of sales prices for each month, meaning the top 10% and bottom 10% of monthly prices are omitted.

Table 2: Descriptive Statistics

This table presents descriptive statistics for the collectibles we use in our study in US dollars (USD). Start and end dates for the data series are in *yyyy* format for the annual data and *yyyymmdd* format for the quarterly data. The mean, maximum, minimum, and return standard deviation are all in percentage points. AC denotes the first-order autocorrelation coefficient.

	Mean	Max	Min	Std. Dev.	Obs	Start Date	End Date	AC
Annual USD								
Blue-Chip Wine	6.78	88.28	-64.66	23.58	107	1901	2007	0.22**
Blue-Chip British Stamps	5.69	73.44	-35.93	15.61	107	1901	2007	0.32***
British Art	5.74	48.27	-58.52	17.24	107	1901	2007	0.31***
Violins	4.80	71.28	-47.79	27.42	107	1901	2007	-0.26***
US Coins	11.73	116.52	-10.32	22.22	40	1968	2007	0.51***
Blue-Chip Paintings	11.44	146.60	-68.70	34.69	107	1901	2007	-0.26***
Blue-Chip Classic Cars	13.41	107.27	-39.21	26.77	27	1981	2007	0.26***
Quarterly USD								
Global Art	0.22	33.40	-20.68	10.77	83	19980331	20180930	-0.55***
Global Paintings	0.18	8.84	-13.09	3.68	83	19980331	20180930	0.64***
Global Prints	0.29	7.30	-13.25	3.86	83	19980331	20180930	0.67***
Global Sculptures	0.18	9.99	-15.64	4.44	83	19980331	20180930	0.48***
Global Photographs	0.25	24.10	-18.75	7.15	83	19980331	20180930	0.41***
Global Drawings	0.67	19.30	-17.68	6.91	83	19980331	20180930	0.52***
Global Old Masters Art	-0.42	22.27	-16.51	6.81	83	19980331	20180930	0.08***
Global 19th C. Art	-0.49	13.36	-13.90	4.94	83	19980331	20180930	0.50***
Global Modern Art	0.07	8.06	-12.98	3.63	83	19980331	20180930	0.60***
Global Post-War Art	0.73	15.15	-11.20	4.83	83	19980331	20180930	0.47***
Global Contemporary Art	0.70	16.91	-16.37	7.33	83	19980331	20180930	0.36***
US Art	0.49	11.57	-13.56	4.06	83	19980331	20180930	0.54***
Liquid Wine	1.71	36.88	-44.89	11.44	80	19980331	20171231	0.22***
Average Artist Paintings	2.39	10.04	-3.68	3.53	81	19980331	20180331	0.48***
Popular Artist Paintings	1.81	15.83	-11.77	5.38	81	19980331	20180331	0.79***
Popular Euro-American Sculptures	1.22	5.29	-0.90	1.26	81	19980331	20180331	0.33***
Jewelry	1.00	4.39	-4.92	2.02	80	19980331	20171231	0.86***
Global Stamps	0.62	3.99	-5.30	2.24	80	19980331	20171231	0.90***
English 18th C. Furniture	-0.80	2.45	-6.71	2.28	80	19980331	20171231	0.90***
Classic Cars	1.73	5.78	-3.98	2.45	80	19980331	20171231	0.90***
Euro-Eastern Rugs/Carpets	-0.64	6.37	-9.82	3.82	80	19980331	20171231	0.81***
English Coins	1.96	6.78	-4.23	2.43	80	19980331	20171231	0.90***
Diamonds	0.41	12.70	-9.29	3.40	54	20040930	20171231	0.30**

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Effect of Autocorrelation Adjustment on Summary Statistics

The table presents additional summary statistics for the USD collectibles returns, focusing on the impact of autocorrelation-adjustment on the geometric average, standard deviation, and cumulative return. If the return series has no statistically significant autocorrelation, there is no adjustment needed for these values so the adjusted statistic is omitted. The averages and standard deviations are annualized and all values are reported in percentage points.

	Arithmetic Average	Geometric Average	Adj. Geometric Average	Standard Deviation	Adj. Standard Deviation	Cumulative Return	Adj. Cumulative Return	Significant Lags
Annual USD (1901 - 2007)								
Blue-Chip Wine	6.78	4.12	-	23.58	-	7421	-	0
Blue-Chip British Stamps	5.69	4.58	3.82	15.61	20.06	11925	5419	1
British Art	5.74	4.18	3.49	17.24	22.05	7890	3811	1
Violins	4.80	1.17	-	27.42	-	246.5	-	0
US Coins	11.73	10.09	7.35	22.22	32.00	4581	1606	1
Blue-Chip Paintings	11.44	6.22	-	34.69	-	63870	-	0
Blue-Chip Classic Cars	13.41	10.55	-	26.77	-	1401	-	0
Specialist	5.06	3.95	-	14.92	-	6232	-	0
Public	7.10	5.20	-	19.60	-	22509	-	0
Quarterly USD (Q1 1998 - Q3 2018)								
Global Art	0.89	-1.37	-	21.55	-	-24.72	-	0
Global Paintings	0.72	0.45	0.11	7.36	11.14	9.70	2.22	1
Global Prints	1.16	0.86	0.47	7.72	11.87	19.50	10.16	1
Global Sculptures	0.72	0.32	-0.05	8.89	12.50	6.89	-1.13	1
Global Photographs	1.02	0.01	-0.81	14.30	19.29	0.27	-15.51	1
Global Drawings	2.69	1.74	0.79	13.82	19.70	43.33	17.71	1
Global Old Masters Art	-1.67	-2.59	-	13.62	-	-41.64	-	0
Global 19th C. Art	-1.95	-2.43	-2.91	9.87	13.95	-39.75	-45.46	1
Global Modern Art	0.28	0.01	-0.30	7.25	10.78	0.27	-5.98	1
Global Post-War Art	2.91	2.46	2.03	9.67	13.45	66.25	52.11	1
Global Contemporary Art	2.79	1.73	0.96	14.66	19.31	43.20	22.06	1
US Art	1.97	1.65	1.29	8.12	11.77	40.60	30.75	1
Liquid Wine	6.82	4.11	-	22.87	-	126.8	-	0
Average Artist Paintings	9.56	9.33	8.88	7.06	11.91	546.9	492.2	2
Popular Artist Paintings	7.25	6.69	5.12	10.77	21.00	283.1	179.0	2
Popular Euro-American Sculptures	4.90	4.87	4.80	2.51	4.60	166.4	162.6	3
Jewelry	3.99	3.91	3.61	4.04	8.83	117.6	105.0	3
Global Stamps	2.50	2.40	1.99	4.47	10.17	61.28	48.70	3
English 18th C. Furniture	-3.19	-3.30	-3.80	4.56	11.08	-48.43	-53.43	4
Classic Cars	6.92	6.81	6.30	4.90	11.33	285.7	249.3	3
Euro-Eastern Rugs/Carpets	-2.57	-2.86	-3.88	7.64	16.25	-43.67	-54.13	3
English Coins	7.83	7.72	7.15	4.86	11.88	361.3	312.6	4
Diamonds	1.63	1.41	-	6.81	-	20.90	-	0
Specialist	5.48	5.25	5.06	6.73	9.31	184.0	173.3	1
Public	2.82	2.72	2.50	4.63	8.16	75.37	67.58	2
Private	-2.95	-3.08	-3.66	5.14	11.95	-46.10	-52.04	4

Table 4: Emotional Yield Estimates: USD Results

This table presents the collectibles emotional yield estimates from the best performing factor mimicking portfolios. *Note: Notation.* Reported EY := $R^{FMP} - R^{C}$ (financial shortfall vs. factor-matched liquid portfolio). The non-pecuniary dividend is $E[R^E] = E[R^{FMP}] - E[R^F] + E[R^T]$. Under $\beta_{C,g}\lambda_g \geq 0$ and $E[R^T] \geq 0$, reported EY is a lower bound for the full economic wedge (see §4.5). We assess mimicking performance with three criteria: (1) the maximum absolute loading (ie: evidence we're using appropriate factors); (2) MAD/$\overline{|\beta|}$ (ie: evidence that the FMP reasonably captures the factor loadings); and (3) the FMP's reduction in residual volatility (ie: evidence we're eliminating uncompensated risk). The 6 considered specifications all use PLS to estimate the factor loadings and entail all combinations of sets of factors (5 or 10 stock-only PCs or stock & bond PCs) with sets of basis assets (stocks & bonds or stocks only).The Specialist, Public, and Private average emotional yield series are constructed ex-post as the equal-weighted average of the underlying collectibles' emotional yield time series, so there is no information provided beyond the average and autocorrelation-adjusted standard error.

	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	max $\lvert\beta_{test}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{test}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	Spec
			Annual USD (1901-2007)				
Blue-Chip Wine	0.86	2.08	17.44	3.93	0.00	0.01	5 BS PC, BS Bas
Blue-Chip British Stamps	1.82	1.69	10.43	2.72	0.04	0.11	5 BS PC, BS Bas
British Art	2.01	1.55	9.41	5.06	0.02	0.08	5 S PC, BS Bas
Violins	2.26	2.65	24.33	1.87	0.14	0.27	5 S PC, BS Bas
US Coins	-0.02	4.94	16.06	3.88	0.15	0.18	5 S PC, S Bas
Blue-Chip Paintings	-4.44	3.33	29.95	3.02	0.02	0.05	5 S PC, BS Bas
Blue-Chip Classic Cars	-2.96	4.89	23.92	2.77	0.02	0.05	5 S PC, BS Bas
Specialist	1.21	1.33					
Public	-1.21	1.90					
			Quarterly USD (Q1 1998 - Q3 2018)				
Global Art	4.43	2.32	20.56	0.38	0.12	0.40	5 S PC, BS Bas
Global Paintings	4.62	0.83	3.88	1.99	0.21	0.47	5 S PC, BS Bas
Global Prints	3.51	0.86	4.37	1.00	0.03	0.14	5 BS PC, BS Bas
Global Sculptures	3.34	0.92	5.26	1.12	0.05	0.21	5 S PC, BS Bas
Global Photographs	4.08	1.84	11.50	1.11	0.05	0.19	5 BS PC, BS Bas
Global Drawings	3.10	2.01	11.35	1.05	0.15	0.37	5 BS PC, BS Bas
Global Old Masters Art	8.31	1.41	12.03	0.60	0.05	0.18	5 S PC, BS Bas
Global 19th C. Art	7.38	1.28	7.14	1.01	0.06	0.24	5 S PC, BS Bas
Global Modern Art	6.27	0.84	4.64	1.76	0.18	0.44	5 S PC, BS Bas
Global Post-War Art	4.85	1.92	6.00	2.54	0.22	0.45	5 S PC, S Bas
Global Contemporary Art	2.31	1.89	12.20	1.06	0.04	0.14	5 S PC, BS Bas
US Art	3.21	0.97	4.81	0.99	0.05	0.20	5 BS PC, BS Bas
Liquid Wine	0.77	2.32	15.79	3.53	0.18	0.35	5 S PC, S Bas
Average Artist Paintings	-2.65	3.14	4.45	2.61	0.24	0.83	10 S PC, S Bas
Popular Artist Paintings	0.74	2.30	7.68	3.43	0.21	0.93	10 BS PC, BS Bas
Popular Euro-American Sculptures	0.17	0.64	1.91	0.20	0.43	1.40	10 BS PC, BS Bas
Jewelry	-0.29	0.86	2.63	0.54	0.17	0.40	5 S PC, BS Bas
Global Stamps	2.75	0.98	3.03	0.62	0.06	0.24	5 S PC, BS Bas
English 18th C. Furniture	12.59	1.14	1.51	0.70	0.17	0.33	5 BS PC, BS Bas
Classic Cars	-2.25	1.25	1.93	1.36	0.33	0.87	10 BS PC, BS Bas
Euro-Eastern Rugs/Carpets	6.50	1.67	6.46	0.44	0.06	0.17	5 S PC, BS Bas
English Coins	0.52	1.10	1.62	1.13	0.16	0.34	5 BS PC, BS Bas
Diamonds	5.29	0.88	6.07	0.25	0.06	0.24	5 S PC, BS Bas
Specialist	0.45	0.88					
Public	2.28	0.78					
Private	9.55	1.21					

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Online Appendix

to accompany

Emotional Yields of Collectibles

This Online Appendix presents additional details on the collectibles price indices, details on the implementation of our factor mimicking portfolio algorithm and autocorrelation-adjustment procedures, information about and results for alternative versions of our price indices (ie: different frequencies or base currencies), and the full results for emotional yield estimates from which we select the version with the best performing factor mimicking portfolio.

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8. Additional Details on the Collectibles Price Indices

Table A1. Collectibles Price Indices in Greater Detail

This table provides greater details about the collectibles price indices used in this study.

Index Name	Data Description
	Panel A. Longer Term
British Art	This annual repeat-sales price index spans 1766-2007 and is denominated in GBP. The index focuses on British paintings and drawings and is provided by Goetzmann, Renneboog, & Spaenjers (2011). The index is based on 1,336 repeated sales identified by merging the Reitlinger (1961) dataset of 6,661 British paintings and drawings with the Renneboog & Spaenjers (2013) dataset of more than 1 million auction sales.
Blue-Chip Paintings	This annual repeat-sales price index spans 1901-2016 and is denominated in USD. The index focuses exclusively on paintings and is provided by Sotheby's. More commonly known as the "Sotheby's Mei Moses" index, this index updates the original 4,896 price pairs of Mei & Moses (2002) to over 80,000 repeat sales in its current form. Mei & Moses (2002) originally focused on all paintings sold at the main sales rooms of Sotheby's and Christie's 1950-2000 (with records in New York), and if a painting had listed in its provenance a prior public sale at any auction house anywhere, they obtained the auction catalogue and recorded the sales price.
Blue-Chip British Stamps	This annual repeat-sales price index spans 1900-2008 and is denominated in GBP. The index begins with the 50 most valuable British stamps in the Stanley Gibbons catalogue in 1900 and adds the missing members of the top 50 most valuable stamps every 9 years, with the basket growing to 127 stamps by the end of the sample. This index is provided by Dimson & Spaenjers (2011).

Blue-Chip Wine	This annual repeat-sales price index spans 1900-2012 and is denominated in GBP. The index focuses on five red Bordeaux wines (the Premier Crus: Haut-Brion, Lafite-Rothschild, Latour, Margaux, and Mouton-Rothschild) and is provided by Dimson, Rousseau, & Spaenjers (2015).
Violins	This annual repeat-sales price index spans 1876-2012 and is denominated in GBP. The index focuses on 320 distinct violins and 1,328 repeat sales and is provided by Graddy & Margolis (2013). Sales prices range from as little as \$50 in 1940 to \$16 million in 2011 (for the "Lady Blunt" Stradivari).
US Coins	This annual repeat-sales price index spans 1968-2012 and is denominated in USD. The index focuses on US coins (pennies, nickels, dimes, quarters, half dollars, and dollars) and is provided by Maslar, Obaid, & Pukthuanthong (2020).
Blue-Chip Classic Cars	This annual capitalization-weighted price index spans 1980-2017 and is denominated in GBP. The index focuses on high-end cars, with the 50 models that are current index constituent having a minimum price of £100,000 and maximum number of survivors at 1,000 units. When the index was formulated in January 2009, the total market cap of the index was £5.2 billion and the average value per vehicle was approximately £285,000. The index was formed in December 2008 and extended backwards. In April 2021, the top 10 index constituents by weight are the Ferrari F40 (8.5%); the McLaren F1 (8.3%); the Ferrari 246 Dino (6.3%); the Ferrari 250 GT SWB Coupe (5.2%); the Porsche Carrera GT 2004-6 (4.9%); the Mercedes-Benz 300 SL Roadster (W 198 II) (4.8%); the Mercedes-Benz 300 SL Coupe (W 198 I) (3.9%); the Ferrari 250 GT SWB California Spider (3.7%); the Porsche 911 RS 2.7 touring (3.2%); and the Ferrari Enzo (3.2%). The index is provided by Historic Automobile Group Inc (HAGI).

Panel B. More Recent

Global Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all Fine Art auction results (paintings, sculptures, drawings, photographs, prints, watercolors, etc.) recorded by Artprice.com except for antiques and furniture, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
US Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all US Fine Art auction results (paintings, sculptures, drawings, photographs, prints, watercolors, etc.) recorded by Artprice.com except for antiques and furniture. The price index is provided by Artprice.com.
Global Paintings	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all painting auction results recorded by Artprice.com, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
Popular Artist Paintings*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - March 2018 and is denominated in USD. The index focuses on paintings (Old Masters, European Impressionists, Modern, and Contemporary) by 100 well-known artists including Basquiat and Canaletto, with public auction data sourced globally accounting for 90% of painting sales by value. The index is provided by Art Market Research.
Average Artist Paintings*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - March 2018 and is denominated in USD. The index measures the average value of paintings sold by the average artist in each month and is provided by Art Market Research. Mechanically, the average "artist price" for over 30,000 artists is first estimated as an exponentially-weighted moving average of 24-month sales prices. The index is then the exponentially-weighted moving average of the entire series of the monthly average artist prices.

Global Prints	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all print auction results recorded by Artprice.com, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
Global Photographs	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all photograph auction results recorded by Artprice.com, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
Global Drawings	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all drawing auction results recorded by Artprice.com, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
Global Sculptures	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all sculpture auction results recorded by Artprice.com, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
Popular Artist European & North American Sculptures*	This monthly exponentially-smoothed moving average sales price index spans January 1985 - March 2018 and is denominated in USD. The index focuses on European & North American sculptures by 100 well-known artists, covering 55,527 works. The index is provided by Art Market Research.
Liquid Wine	This monthly value-weighted price index spans January 1988 - December 2017 and is denominated in GBP. The index focuses on Bordeaux red wines from 24 leading chateaux, and the 100 highest-rated wines (in terms of Robert Parker Jr. scores) trading on the Liv-ex exchange are included in the basket. Scarcity weights give an approximate "value-weighted" interpretation and the basket is priced using the Liv-ex Mid Price, the midpoint between the current highest bid price and lowest offer price on the Liv-ex trading platform. The index is provided by Liv-ex.

Global Stamps*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - December 2017 and is denominated in USD. The index focuses on many genres of stamps: Great Britain Classics; Great Britain 20th Century; British Europe; British Asia; Australia States; Australia; Australasia; France Classics; France 20th Century; French Colonies; German States; Germany; Germany Post-1945; Italian States; Italy; Spain Classic Issues; Spain 20th Century; China; China People's Republic; Taiwan; Middle East; Saudi Arabia; United States Classics; United States Middle to Modern; and United States Post-1945. The index is provided by Art Market Research.
English Coins*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - December 2017 and is denominated in USD. The index focuses on several types of English coins: English Hammered Coins [gold]; English Hammered Coins [silver]; English Milled Coins [gold]; and English Milled Coins [silver]. The index is provided by Art Market Research.
Classic Cars*	This monthly exponentially-smoothed moving average sales price index spans January 1981 - December 2017 and is denominated in USD. The index focuses on several types of classic cars: Alfa Romeo; Aston Martin; Bentley; BMW; Ferrari; Ford; Jaguar; Lamborghini; Lotus; Maserati; Mercedes-Benz; MG; Porsche; Rolls-Royce; and Triumph. The index is provided by Art Market Research.
Jewelry*	This monthly exponentially-smoothed moving average sales price index spans January 1986 - December 2017 and is denominated in USD. The index focuses on several broad genres of jewelry: 1945-1975 jewelry; antique jewelry; Belle Epogue & Art Deco; and pearl jewelry. The index is provided by Art Market Research.

General Diamonds	This daily value-weighted price index spans January 1, 2004 to January 31, 2018 and is denominated in USD. The index focuses on 300 stone profiles that accounted for approximately 43% of the total market in dollar value at the time of the index composition. The polished diamonds are eligible for inclusion if they are a single stone, have a 'cut' value, have a 'carat' of at least 1/10 and less than 10, have a 'color' value of D-P, have a 'clarity' value of IF to I3, and have a 'price pc' value. The index is provided by IDEX.
European & Eastern Rugs & Carpets*	This monthly exponentially-smoothed moving average sales price index spans January 1985 - December 2017 and is denominated in USD. The index focuses on European and Eastern Rugs & Carpets sold at auction. The index is provided by Art Market Research.
English 18th Century Furniture*	This monthly exponentially-smoothed moving average sales price index spans January 1976 - December 2017 and is denominated in USD. The index focuses on many genres of English 18th Century furniture: Settes, Sofas, Day-Beds; Sideboards; Stools; Tables [Folding Card & Tea]; Tables [Dining]; Tables [Pembroke]; Side-Tables; Console Tables; Bonnheurs-du-Jour; Book-Cases; Bureaux; Bureaux-Bookcases; Chairs 1700-1750; Chippendale Chairs; Hepplewhite Chairs; Sheraton Chairs; Upholstered Arm-Chairs; Chests 1700-1720; Chests of Drawers 1700-1720; Chests on Stands; Chests of Drawers 1721-1760; Chests on Chests; Serpentine & Bow-Fronted Chests; Straight-Fronted Chests; Clothes Presses; Hanging Corner Cupboards; Standing Corner Cupboards; Desks; Dressers; Dressers [Enclosed Fronts]; Dressers [Open Below]; Dressing Table; Dressing Tables [Knee-Hole]; Mirrors [Toilet]; Mirrors [Wall & Pier Glass]; and Secretaire Book-Cases. The index is provided by Art Market Research.

Global Old Masters Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all Old Masters Fine Art auction results (paintings, sculptures, drawings, photographs, prints, watercolors, etc.) recorded by Artprice.com except for antiques and furniture, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
Global 19th Century Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all 19th Century Fine Art auction results (paintings, sculptures, drawings, photographs, prints, watercolors, etc.) recorded by Artprice.com except for antiques and furniture, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
Global Modern Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all Modern Art Fine Art auction results (paintings, sculptures, drawings, photographs, prints, watercolors, etc.) recorded by Artprice.com except for antiques and furniture, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.
Global Post-War Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all Post-War Fine Art auction results (paintings, sculptures, drawings, photographs, prints, watercolors, etc.) recorded by Artprice.com except for antiques and furniture, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.

Global Contemporary Art	This quarterly repeat-sales price index spans Q4 1997 - Q3 2018 and is denominated in USD. The index focuses on all Contemporary Fine Art auction results (paintings, sculptures, drawings, photographs, prints, watercolors, etc.) recorded by Artprice.com except for antiques and furniture, and compiles auction sales from over 6,300 auction houses globally. The price index is provided by Artprice.com.

* In constructing the index, Art Market Research includes only the central 80% of sales prices for each month, meaning the top 10% and bottom 10% of monthly prices are omitted.

A Additional Estimation Details

This section provides additional details about the implementation of our factor mimicking approach to the data. In particular, this section discusses how we implement the numerical approach to our portfolio optimization problem, how we select the basis sets, how we autocorrelation-adjust the standard deviations and compound total returns.

A1. Numerical Solution to Portfolio Problem

We solve the portfolio problem numerically using a random search. As Bergstra & Bengio (2012) find, granting random search the same computational budget as grid search and manual search, random search selects a better solution. Mechanically, we randomly sample N weights from a diffuse Dirichlet distribution. The Dirichlet distribution's support is the space of simplexes, that is, non-negative vectors that sum to one, and our diffuse parametrization is equivalent to a multivariate uniform prior (ie: $\omega_i = \frac{1}{N}\ ,\ i \in 1, \ldots, N$). We then compute the value of the objective function for the chosen value of κ. Repeating this procedure millions of times (currently 3 million times), we choose the N-dimensional vector of weights that minimizes the objective function.

A2. Basis Set Selection

We desire a parsimonious basis set for two reasons: (1) interpretability; and (2) computational feasibility. To select a basis set, we begin with US stocks and US government bonds whenever these two basis sets are eligible. We then compute the intercept (alpha/mispricing) from regressing each non-chosen basis asset on the selected basis assets. The asset with the largest absolute pricing error is then added to the set of selected basis assets. This procedure is repeated until either: (1) there are no more unselected, eligible basis assets; or (2) there are 16 selected basis assets. When the set of eligible basis assets includes both stocks and bonds, stocks and bonds are each limited to being half of the total set of basis assets.

These regressions include a long-only constraint to mirror the procedure of using these basis assets to replicate the test asset. Instead using traditional "spanning tests" leads to a poorly performing set of basis assets because unconstrained weights in the spanning tests become constrained weights for the FMPs.

A3. Handling Autocorrelation for Summary Statistics

Vorsatz (2020) extends French, Schwert, and Stambaugh (1987), proposing that the unconditional variance be estimated as:

$$\widehat{\sigma}_t^2 = (r_t - \bar{r})^2 + 2\sum_{k=1}^{L}(r_t - \bar{r})(r_{t-k} - \bar{r})$$
$$\widehat{\sigma}^2 = \frac{1}{N-L-1}\sum_{t=1}^{N-L-1}\widehat{\sigma}_t^2$$

where L is the number of statistically significant autocorrelation lags and division by $(N - L - 1)$ ensures unbiasedness.

Vorsatz (2020) also provides a means for estimating autocorrelation-adjusted total returns based on a second-order Taylor series expansion. We reproduce the approximation strategy below.

Let P_0 denote the value of the price index at time 0, which is inclusive of any dividends or coupon payments. The compound total return from time 0 to T is thus:

$$\frac{P_T}{P_0} - 1 \tag{12}$$

Define the gross return from time $t-1$ to t as $R_t = \frac{P_t}{P_{t-1}}$. Note that

$$\frac{P_T}{P_0} = \prod_{t=1}^{T} R_t$$
$$\implies \log\left(\frac{P_T}{P_0}\right) = \sum_{t=1}^{T}\log(R_t) \tag{13}$$

Since the second-order Taylor series expansion of $\log(R_t)$ centered at $R_t = \bar{R}$ is:[18]

$$\log(R_t) = \log(\bar{R}) + \frac{1}{\bar{R}}(R_t - \bar{R}) - \frac{1}{2\bar{R}^2}(R_t - \bar{R})^2$$

[18] Note that the Taylor series expansion of a real function $f(x)$ about a point $x = a$ is given by:

$$f(x) = f(a) + f'(a)(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \frac{f^{(3)}(a)}{3!}(x-a)^3 + \cdots + \frac{f^{(n)}(a)}{n!}(x-a)^n + \ldots$$

equation (13) can be rewritten as:

$$
\begin{aligned}
\log\left(\frac{P_T}{P_0}\right) &= \sum_{t=1}^{T}\log(\bar{R}) + \frac{1}{\bar{R}}\sum_{t=1}^{T}(R_t - \bar{R}) - \frac{1}{2\bar{R}^2}\sum_{t=1}^{T}(R_t - \bar{R})^2 \\
\implies \frac{1}{T}\log\left(\frac{P_T}{P_0}\right) &= \log(\bar{R}) - \frac{1}{2\bar{R}^2}\frac{1}{T}\sum_{t=1}^{T}(R_t - \bar{R})^2 \\
\implies \frac{1}{T}\log\left(\frac{P_T}{P_0}\right) &= \log(\bar{R}) - \frac{1}{2\bar{R}^2}\frac{T-1}{T}\widehat{\sigma}^2 \qquad (14)
\end{aligned}
$$

where $\widehat{\sigma}^2 = \frac{1}{T-1}\sum_{t=1}^{T}(R_t - \bar{R})^2$ is the unbiased estimate of the sample variance. Solving equation (14) for the compound total return in equation (12) yields:

$$
\frac{P_T}{P_0} - 1 = \exp\left(T\log(\bar{R}) - \frac{T-1}{2\bar{R}^2}\widehat{\sigma}^2\right) - 1 \qquad (15)
$$

Since the collectibles price indices are smoothed, equation (12) provides an unreliable estimate of the compound total return. A better estimate of the compound total return comes from substituting the autocorrelation-adjusted variance estimate into equation (15).

A4. Relating Rental Yields to Emotional Yields

Let P be market value. Rental platforms quote an annual rental yield ϕ (so the fee is $\approx \phi P$). For direct ownership, your emotional yield E (non-pecuniary utility flow) is not the same object as ϕ, but they are related:

$$E \approx \phi - (\text{platform \& logistics margin}) - (\text{insurance/storage}) - (\text{liquidity/availability premium}).$$

This equation implies rental fees monetize display/possession services for non-owners; owners internalize a similar service flow as E. After costs and margins, ϕ provides a plausible upper-bound reference for mid-tier emotional value, consistent with your blue-chip E being positive but typically lower than rentalized mid-tier rates, and far below the heuristic "infinite" utility of sentimental heirlooms. This is fully consistent with the unconditional framework and avoids re-estimating anything.

B Results for Additional Return Series

This section includes additional results for additional quarterly USD return series not included in the paper and for monthly (USD & GBP) and annual (GBP) versions of the return series. These additional results are cumulative log return figures, the exponentially-smoothed emotional yield estimates, descriptive statistics, autocorrelation-adjusted summary statistics, and the emotional yield point estimates.

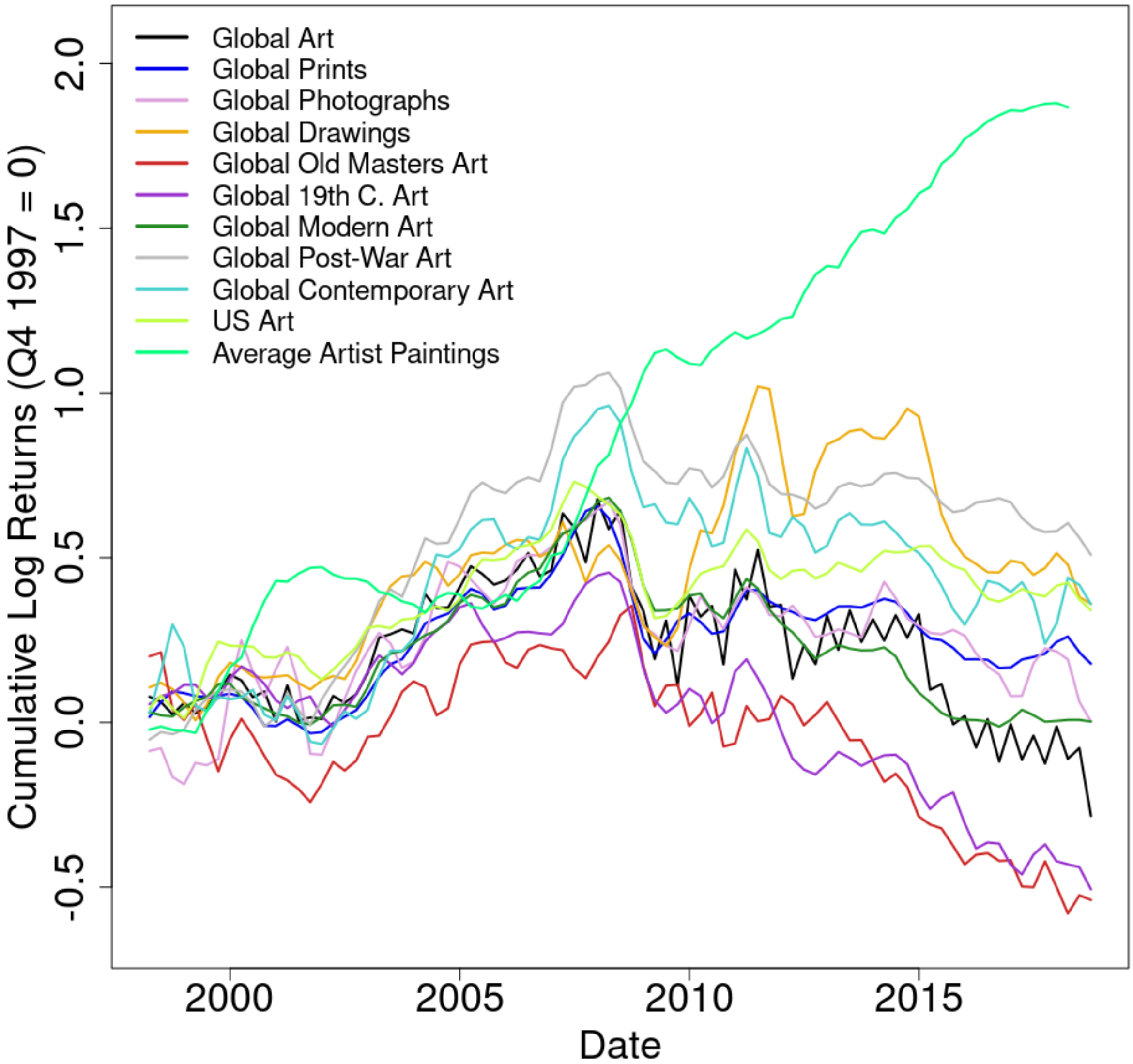

Figure A1: **Cumulative Log Returns for Additional Quarterly USD Series**

This figure plots the cumulative log returns of additional quarterly USD collectibles over the Q1 1998–Q3 2018 time period. Q4 1997 is scaled to have a cumulative log return of 0.

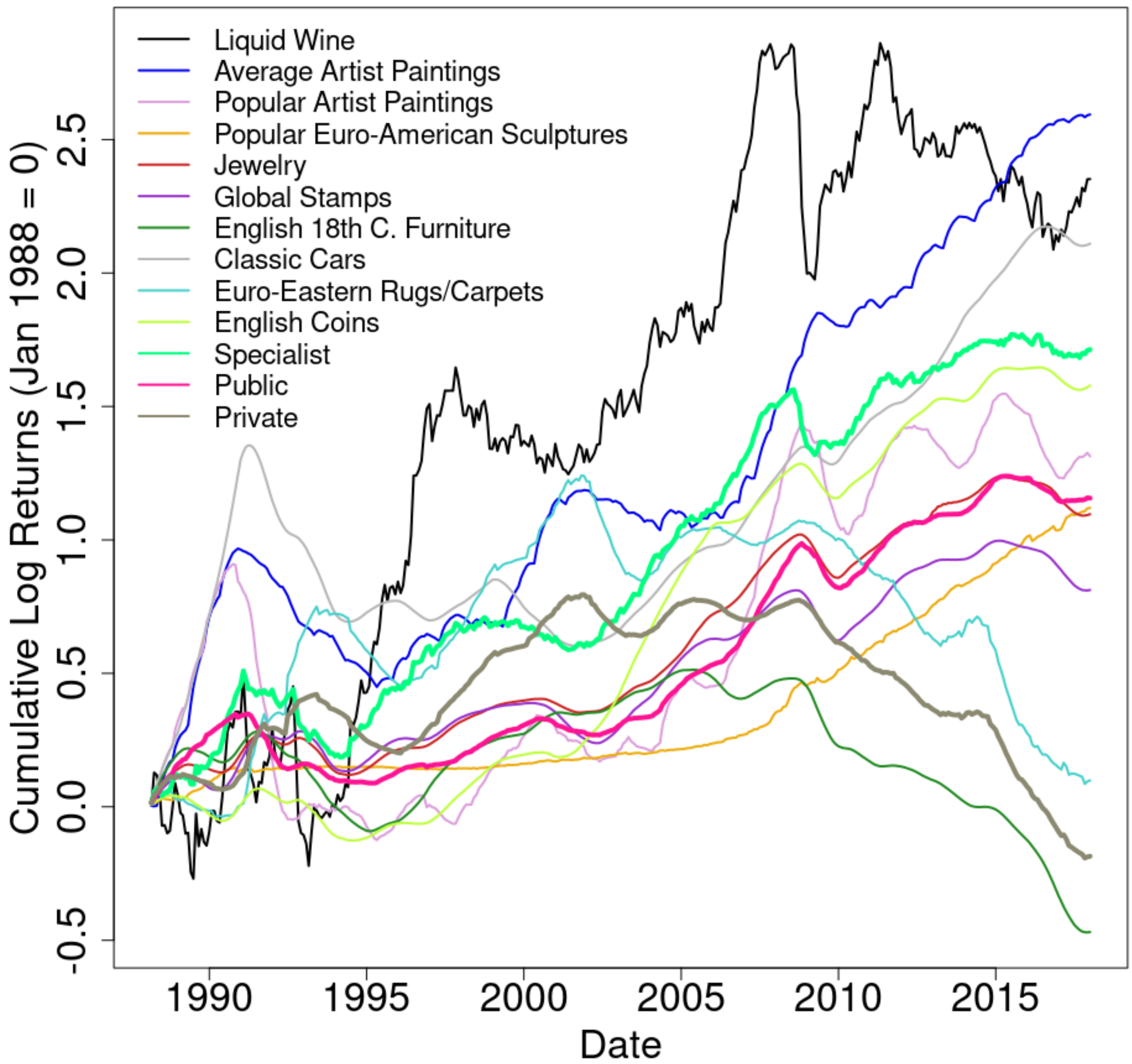

Figure A2: **Cumulative Log Returns for Monthly USD Series**

This figure plots the cumulative log returns of monthly USD collectibles over the February 1988 - December 2017 time period. January 1988 is scaled to have a cumulative log return of 0. The Specialist, Public, and Private series are cumulative equal-weighted averages of the non-missing log returns for groups of similar collectibles. Specialist-domain collectibles include liquid wine, global stamps, classic cars, and English coins. Public-domain collectibles include popular artist paintings, popular artist European & North American sculptures, jewelry, and diamonds. Private-domain collectibles include English 18th century furniture and European & Eastern Rugs & Carpets.

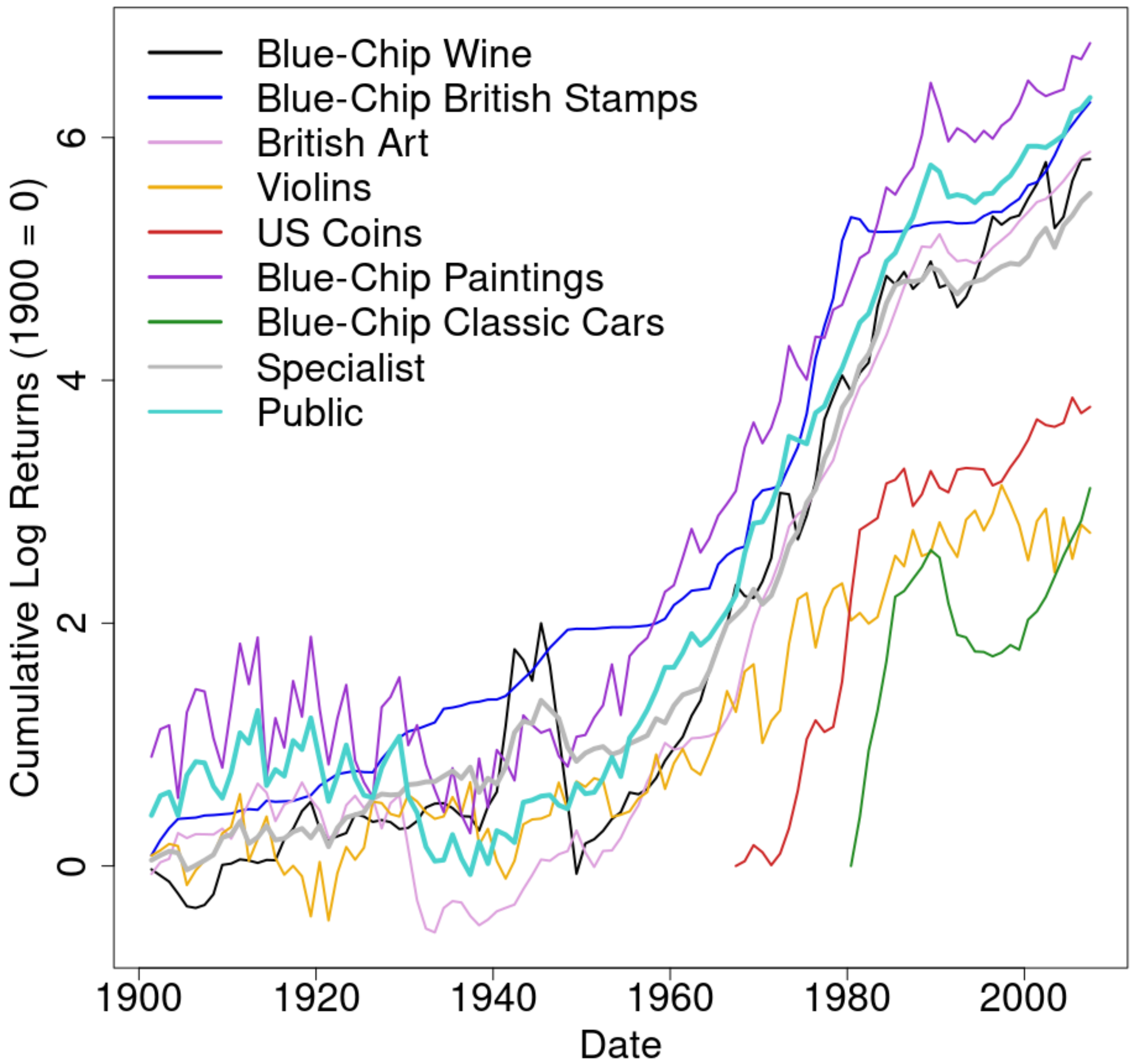

Figure A3: **Cumulative Log Returns for Annual GBP Series**

This figure plots the cumulative log returns of annual GBP collectibles over the 1900-2007 time period. 1900 is scaled to have a cumulative log return of 0.

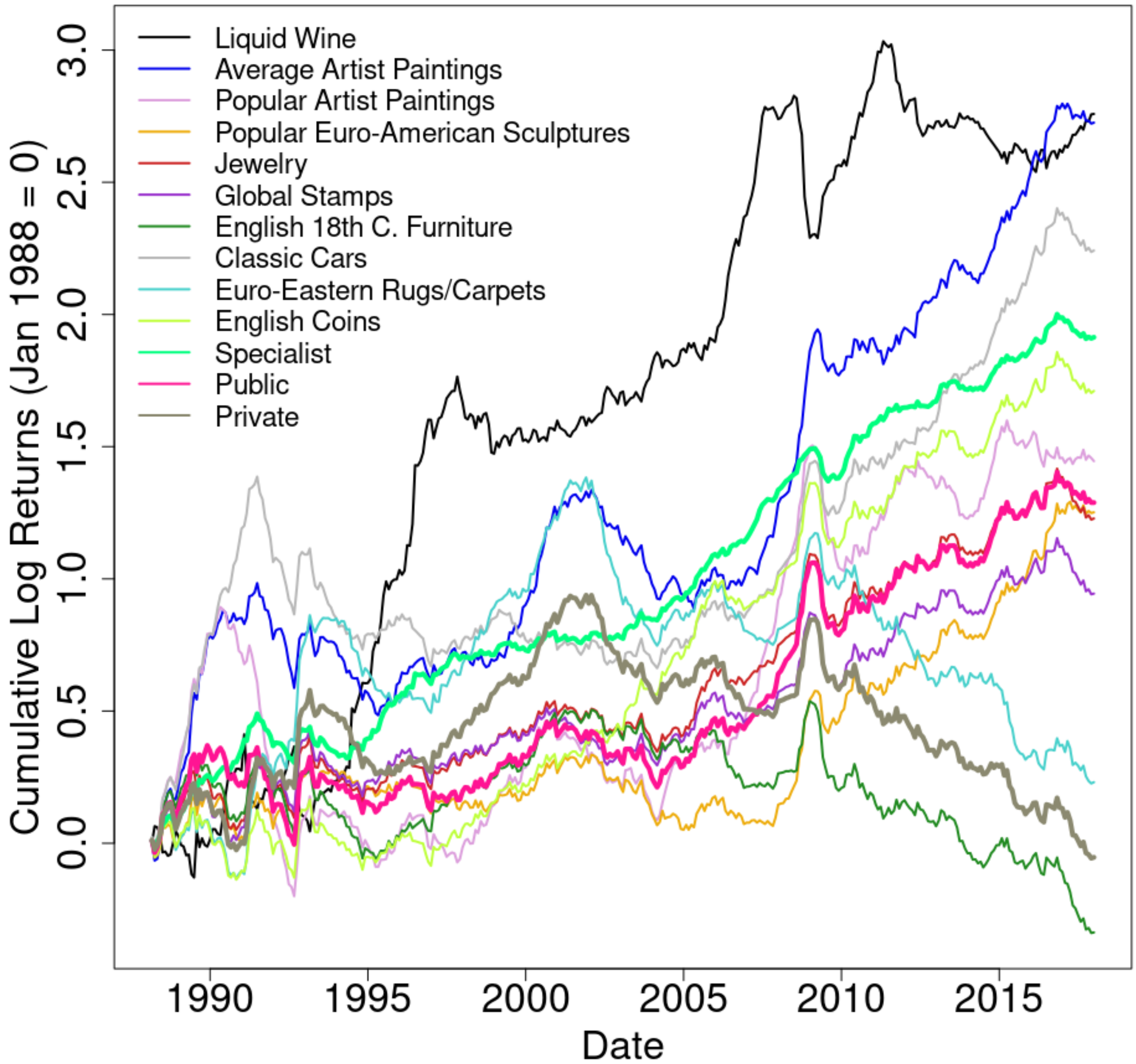

Figure A4: **Cumulative Log Returns for Monthly GBP Series**

This figure plots the cumulative log returns of monthly GBP collectibles over the February 1988 - December 2017 time period. January 1988 is scaled to have a cumulative log return of 0.

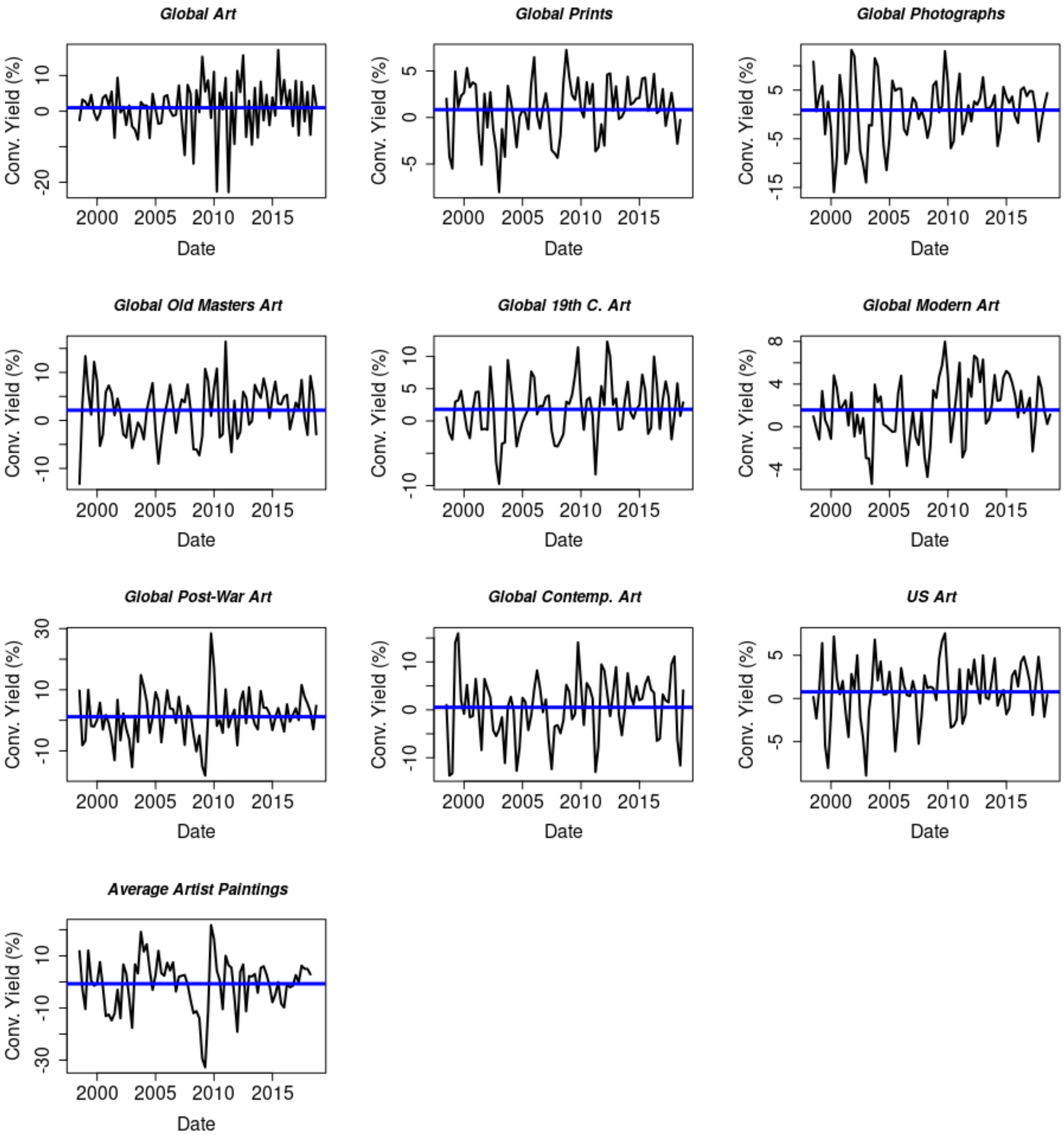

Figure A5: **Exponentially-Smoothed Emotional Yields for Additional Quarterly USD Returns**

This figure plots the exponentially-smoothed emotional yields of additional quarterly USD collectibles over the Q1 1998 - Q3 2018 time period. The exponential smoothing function takes the form $s_t = \alpha x_t + (1-\alpha)s_{t-1}$, where x_t is the estimated emotional yield for period t. We set $\alpha = 0.2$ to allow for a moderate degree of smoothing.

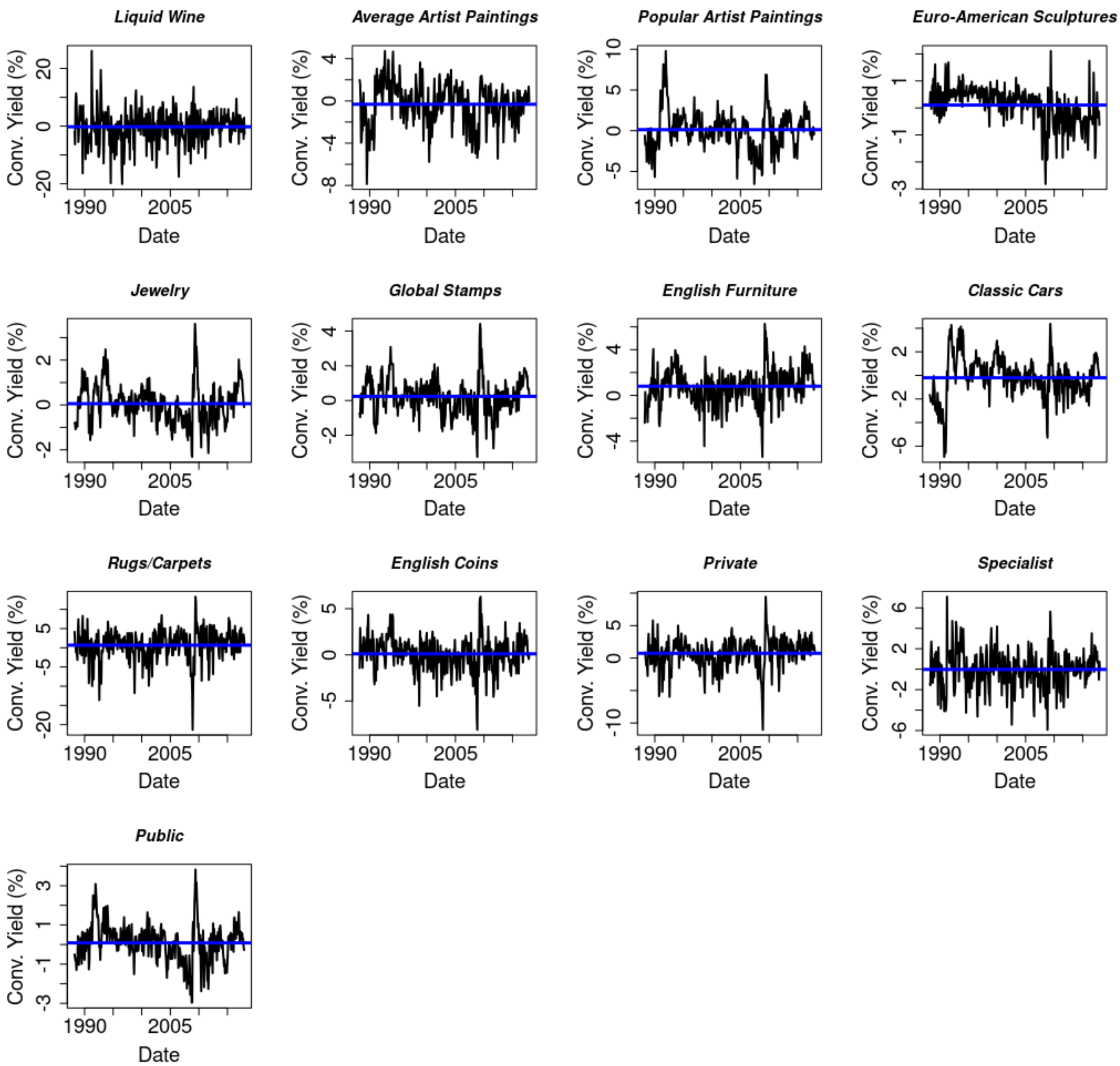

Figure A6: **Exponentially-Smoothed Emotional Yields for Monthly USD Returns**

This figure plots the exponentially-smoothed emotional yields of the monthly USD collectibles over the February 1988 - December 2017 time period. The exponential smoothing function takes the form $s_t = \alpha x_t + (1-\alpha)s_{t-1}$, where x_t is the estimated emotional yield for period t. We set $\alpha = 0.2$ to allow for a moderate degree of smoothing. The Specialist, Public, and Private series are equal-weighted averages of the non-missing emotional yields for groups of similar collectibles. Specialist-domain collectibles include liquid wine, global stamps, classic cars, and English coins. Public-domain collectibles include popular artist paintings, popular artist European & North American sculptures, jewelry, and diamonds. Private-domain collectibles include English 18th century furniture and European & Eastern Rugs & Carpets.

Table A2: Descriptive Statistics: Annual GBP & Monthly Returns

This table presents additional descriptive statistics for the annual GBP collectibles returns and the monthly (USD & GBP) collectibles returns. Start and end dates for the data series are in *yyyy* format for the annual data and *yyyymmdd* format for the quarterly data. The mean, maximum, minimum, and return standard deviation are all in percentage points. AC denotes the first-order autocorrelation coefficient.

	Mean	Max	Min	Std. Dev.	Obs	Start Date	End Date	AC
				Annual GBP				
Blue-Chip Wine	7.82	88.28	-44.40	22.16	107	1901	2007	0.26 ***
Blue-Chip British Stamps	6.50	60.54	-9.18	10.63	107	1901	2007	0.56 ***
British Art	6.54	40.20	-35.38	13.24	107	1901	2007	0.42 ***
Violins	5.38	73.17	-47.68	23.81	107	1901	2007	-0.29 ***
US Coins	12.01	99.56	-26.51	23.79	40	1968	2007	0.47 ***
Blue-Chip Paintings	11.96	145.84	-68.68	35.58	107	1901	2007	-0.28 ***
Blue-Chip Classic Cars	14.72	72.64	-31.28	24.96	27	1981	2007	0.64 ***
				Monthly USD				
Liquid Wine	0.88	27.97	-29.14	6.60	359	19880229	20171231	0.14 **
Average Artist Paintings	0.74	8.19	-2.62	1.70	359	19880229	20171231	0.69***
Popular Artist Paintings	0.39	8.68	-9.77	2.33	359	19880229	20171231	0.78***
Popular Euro-American Sculptures	0.31	2.70	-2.06	0.55	359	19880229	20171231	0.34 ***
Jewelry	0.31	1.84	-1.72	0.69	359	19880229	20171231	0.95***
Global Stamps	0.23	2.14	-1.93	0.76	359	19880229	20171231	0.98***
English 18th C. Furniture	-0.13	2.51	-2.43	0.88	359	19880229	20171231	0.97***
Classic Cars	0.60	5.88	-3.31	1.51	359	19880229	20171231	0.98***
Euro-Eastern Rugs/Carpets	0.04	15.27	-5.47	1.83	359	19880229	20171231	0.51***
English Coins	0.44	2.24	-1.50	0.81	359	19880229	20171231	0.98 ***
				Monthly GBP				
Liquid Wine	0.86	25.21	-20.92	4.37	359	19880229	20171231	0.19***
Average Artist Paintings	0.82	15.84	-9.05	3.39	359	19880229	20171231	0.24***
Popular Artist Paintings	0.47	13.60	-13.50	3.69	359	19880229	20171231	0.36 ***
Popular Euro-American Sculptures	0.39	13.55	-9.99	2.89	359	19880229	20171231	0.08***
Jewelry	0.38	14.04	-10.57	2.88	359	19880229	20171231	0.14 ***
Global Stamps	0.30	14.13	-10.73	2.87	359	19880229	20171231	0.14 **
English 18th C. Furniture	-0.05	12.92	-11.16	2.89	359	19880229	20171231	0.16***
Classic Cars	0.67	12.86	-9.88	3.13	359	19880229	20171231	0.26***
Euro-Eastern Rugs/Carpets	0.12	19.14	-9.28	3.39	359	19880229	20171231	0.25***
English Coins	0.52	13.73	-10.36	2.89	359	19880229	20171231	0.14 ***

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A3: Effect of Autocorrelation Adjustment on Summary Statistics: Annual GBP & Monthly Returns

The table presents additional summary statistics for the annual GBP collectibles returns and the monthly (USD & GBP) collectibles returns, focusing on the impact of autocorrelation-adjustment on the geometric average, standard deviation, and cumulative return. If the return series has no statistically significant autocorrelation, there is no adjustment needed for these values so the adjusted statistic is omitted. The averages and standard deviations are annualized and all values are reported in percentage points.

	Arithmetic Average	Geometric Average	Adj. Geometric Average	Standard Deviation	Adj. Standard Deviation	Cumulative Return	Adj. Cumulative Return	Significant Lags
Annual GBP (1901 - 2007)								
Blue-Chip Wine	7.82	5.59	4.44	22.16	27.35	33658	10339	1
Blue-Chip British Stamps	6.50	6.06	4.33	10.63	21.73	53879	9198	4
British Art	6.54	5.65	5.05	13.24	17.96	35764	19275	1
Violins	5.38	2.60	-	23.81	-	1455	-	0
US Coins	12.01	9.91	7.24	23.79	33.46	4288	1536	1
Blue-Chip Paintings	11.96	6.54	-	35.58	-	87693	-	0
Blue-Chip Classic Cars	14.72	12.22	8.90	24.96	37.75	2147	898.3	1
Specialist	5.86	5.31	-	10.77	-	25380	-	0
Public	7.74	6.09	-	18.28	-	56013	-	0
Monthly USD (Feb 1988 - Dec 2017)								
Liquid Wine	10.51	7.89	-	22.86	-	950.5	-	0
Average Artist Paintings	8.87	8.70	6.89	5.90	20.00	1238	681.7	14
Popular Artist Paintings	4.73	4.40	1.04	8.09	27.28	271.9	36.30	10
Popular Euro-American Sculptures	3.77	3.75	3.65	1.90	4.89	206.4	197.3	11
Jewelry	3.70	3.67	3.36	2.39	8.24	199.3	173.0	10
Global Stamps	2.75	2.72	2.31	2.63	9.48	125.3	99.18	10
English 18th C. Furniture	-1.52	-1.57	-2.35	3.04	12.88	-37.46	-50.52	19
Classic Cars	7.21	7.07	4.70	5.24	22.52	724.8	306.5	19
Euro-Eastern Rugs/Carpets	0.53	0.33	-1.34	6.32	19.34	10.39	-32.97	11
English Coins	5.33	5.29	4.53	2.81	12.66	384.9	287.1	20
Specialist	5.93	5.74	5.45	6.12	9.81	454.7	408.6	4
Public	3.91	3.87	3.43	2.84	9.84	217.9	178.7	11
Private	-0.55	-0.62	-1.54	3.80	14.12	-16.91	-36.96	17
Monthly GBP (Feb 1988 - Dec 2017)								
Liquid Wine	10.38	9.26	8.81	15.14	17.81	1478	1282	1
Average Artist Paintings	9.82	9.15	8.37	11.73	17.08	1426	1114	3
Popular Artist Paintings	5.65	4.84	2.36	12.79	25.78	324.3	102.3	6
Popular Euro-American Sculptures	4.68	4.19	-	10.00	-	249.6	-	0
Jewelry	4.60	4.11	3.97	9.98	11.30	241.6	227.2	1
Global Stamps	3.65	3.16	-	9.94	-	157.1	-	0
English 18th C. Furniture	-0.63	-1.13	-1.29	10.02	11.50	-28.6	-32.0	1
Classic Cars	8.09	7.52	6.72	10.84	16.68	841.1	641.6	3
Euro-Eastern Rugs/Carpets	1.44	0.77	-0.48	11.74	19.66	25.96	-13.35	4
English Coins	6.22	5.73	5.59	10.00	11.35	453.2	429.8	1
Specialist	6.56	6.41	6.36	5.48	6.39	577.9	567.1	1
Public	4.82	4.31	4.17	10.17	11.51	262.7	247.0	1
Private	0.36	-0.18	-0.39	10.44	12.24	-5.19	-11.00	1

Table A4: Emotional Yield Estimates: Annual GBP & Monthly Results

This table presents the collectibles emotional yield estimates from the best performing factor mimicking portfolios. We assess mimicking performance with three criteria: (1) the maximum absolute loading (ie: evidence we're using appropriate factors); (2) MAD/$\overline{|\beta|}$ (ie: evidence that the FMP reasonably captures the factor loadings); and (3) the FMP's reduction in residual volatility (ie: evidence we're eliminating uncompensated risk). The 6 considered specifications all use PLS to estimate the factor loadings and entail all combinations of sets of factors (5 or 10 stock-only PCs or stock & bond PCs) with sets of basis assets (stocks & bonds or stocks only).The Specialist, Public, and Private average emotional yield series are constructed ex-post as the equal-weighted average of the underlying collectibles' emotional yield time series, so there is no information provided beyond the average and autocorrelation-adjusted standard error.

	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\|\beta_{test}\|$	$\frac{\text{MAD}}{\max\|\beta_{test}\|}$	$\frac{\text{MAD}}{\overline{\|\beta\|}}$	Spec
			Annual GBP (1901-2007)				
Blue-Chip Wine	0.93	2.27	18.30	5.30	0.04	0.19	10 S PC, S Bas
Blue-Chip British Stamps	-1.46	1.98	8.76	1.04	0.05	0.11	5 S PC, BS Bas
British Art	0.93	1.55	8.56	3.31	0.01	0.06	5 S PC, BS Bas
Violins	1.37	2.33	21.58	1.58	0.31	0.82	5 BS PC, BS Bas
US Coins	-2.35	4.74	19.82	2.67	0.03	0.06	5 S PC, BS Bas
Blue-Chip Paintings	-3.72	3.35	30.12	3.49	0.03	0.05	5 S PC, BS Bas
Blue-Chip Classic Cars	-3.35	6.14	18.32	4.06	0.02	0.08	5 S PC, BS Bas
			Monthly USD (Feb 1988 - Dec 2017)				
Liquid Wine	-2.86	1.26	12.25	2.76	0.31	0.51	5 S PC, S Bas
Average Artist Paintings	-3.74	1.12	2.96	1.68	0.24	0.86	10 BS PC, BS Bas
Popular Artist Paintings	1.55	1.36	5.74	1.10	0.27	0.68	5 BS PC, BS Bas
Popular Euro-American Sculptures	1.27	0.38	1.24	0.11	0.58	1.19	5 BS PC, BS Bas
Jewelry	0.70	0.43	1.34	0.42	0.27	0.64	5 BS PC, BS Bas
Global Stamps	2.86	0.47	1.47	0.53	0.25	0.71	10 BS PC, BS Bas
English 18th C. Furniture	9.59	0.69	0.32	1.02	0.22	0.54	10 BS PC, BS Bas
Classic Cars	-2.39	1.13	2.15	0.46	0.29	0.55	5 BS PC, BS Bas
Euro-Eastern Rugs/Carpets	8.45	1.25	4.05	1.87	0.47	0.74	5 S PC, S Bas
English Coins	1.40	0.63	0.38	1.53	0.33	0.67	10 S PC, BS Bas
Specialist	-0.20	0.55					
Public	1.05	0.52					
Private	8.78	0.85					
			Monthly GBP (Feb 1988 - Dec 2017)				
Liquid Wine	0.08	1.16	10.04	3.20	0.18	0.86	10 S PC, S Bas
Average Artist Paintings	-1.83	1.18	6.89	2.44	0.27	0.68	10 S PC, S Bas
Popular Artist Paintings	0.69	1.37	11.13	0.37	0.38	0.82	10 S PC, BS Bas
Popular Euro-American Sculptures	0.89	0.49	7.20	2.51	0.16	0.77	10 S PC, BS Bas
Jewelry	1.93	0.58	6.04	3.12	0.15	0.69	10 S PC, BS Bas
Global Stamps	2.97	0.49	6.58	2.03	0.17	0.63	10 S PC, BS Bas
English 18th C. Furniture	7.48	0.62	6.44	2.13	0.19	0.65	10 S PC, BS Bas
Classic Cars	-1.24	0.95	6.89	2.70	0.22	0.76	10 S PC, BS Bas
Euro-Eastern Rugs/Carpets	6.08	1.01	5.89	5.05	0.15	0.63	10 S PC, BS Bas
English Coins	0.01	0.64	6.24	3.12	0.15	0.74	10 S PC, BS Bas

C Additional Estimation Details

This section presents the diagnostic results for the six-factor mimicking portfolios (FMPs) we consider for each return series. We assess mimicking performance with three criteria: (1) the maximum absolute loading (i.e., evidence we're using appropriate factors); (2) MAD/$\overline{|\beta|}$ (i.e., evidence that the FMP reasonably captures the factor loadings); and (3) the FMP's reduction in residual volatility (i.e., evidence we're eliminating uncompensated risk). The six considered specifications all use PLS to estimate the factor loadings and entail all combinations of sets of factors (5 or 10 stock-only PCs or stock & bond PCs) with sets of basis assets (stocks & bonds or stocks only). From these options, we choose the FMP that performs best in terms of these three dimensions, without regard for the actual point estimate of the emotional yield. Notably, the emotional yield estimates are generally quite stable across reasonable-performing FMPs.

Table A5: Emotional Yield Estimates: All USD Specifications

This table shows all of the estimated model specifications for the emotional yields of the USD collectibles.

Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\lvert\overline{\beta}\rvert}$	**Spec**
Annual USD (1901–2007)							
Blue-Chip Wine	0.86	2.08	17.44	3.93	0.00	0.01	5 BS PC, BS Bas
Blue-Chip Wine	1.43	2.15	18.22	4.07	0.09	0.34	5 S PC, S Bas
Blue-Chip Wine	1.56	2.08	17.50	4.07	0.01	0.02	5 S PC, BS Bas
Blue-Chip Wine	1.14	2.08	17.86	4.07	0.05	0.26	10 BS PC, BS Bas
Blue-Chip Wine	1.67	2.11	18.59	4.21	0.08	0.46	10 S PC, S Bas
Blue-Chip Wine	0.70	2.09	18.13	4.21	0.10	0.58	10 S PC, BS Bas
Blue-Chip British Stamps	1.82	1.69	10.43	2.72	0.04	0.11	5 BS PC, BS Bas
Blue-Chip British Stamps	2.22	1.93	10.84	3.25	0.16	0.61	5 S PC, S Bas
Blue-Chip British Stamps	2.25	1.65	8.98	4.86	0.22	0.46	5 S PC, BS Bas
Blue-Chip British Stamps	2.19	1.69	10.78	3.39	0.07	0.32	10 BS PC, BS Bas
Blue-Chip British Stamps	2.35	1.85	12.73	3.34	0.11	0.59	10 S PC, S Bas
Blue-Chip British Stamps	1.21	1.71	11.78	3.34	0.12	0.63	10 S PC, BS Bas
British Art	2.89	1.49	9.54	4.88	0.02	0.09	5 BS PC, BS Bas
British Art	2.60	1.53	11.61	5.06	0.03	0.13	5 S PC, S Bas
British Art	2.01	1.55	9.41	5.06	0.02	0.08	5 S PC, BS Bas
British Art	2.58	1.52	10.10	4.98	0.05	0.32	10 BS PC, BS Bas
British Art	2.35	1.56	12.13	5.06	0.04	0.32	10 S PC, S Bas
British Art	2.22	1.58	11.02	5.06	0.10	0.72	10 S PC, BS Bas
Violins	0.52	2.63	26.70	0.56	0.15	0.27	5 BS PC, BS Bas
Violins	3.56	2.89	24.99	1.87	0.43	0.82	5 S PC, S Bas
Violins	2.26	2.65	24.33	1.87	0.14	0.27	5 S PC, BS Bas
Violins	1.57	2.63	26.21	0.85	0.21	0.47	10 BS PC, BS Bas
Violins	3.49	2.85	25.61	2.27	0.25	0.61	10 S PC, S Bas
Violins	2.31	2.65	24.45	2.27	0.25	0.60	10 S PC, BS Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
US Coins	-3.26	4.72	20.09	1.58	0.37	0.94	5 BS PC, BS Bas
US Coins	-0.02	4.94	16.06	3.88	0.15	0.18	5 S PC, S Bas
US Coins	-2.06	4.85	17.59	3.88	0.46	0.58	5 S PC, BS Bas
US Coins	-3.29	4.72	20.29	1.64	0.27	1.03	10 BS PC, BS Bas
US Coins	-0.65	4.98	18.59	5.02	0.22	0.44	10 S PC, S Bas
US Coins	-1.32	4.87	15.96	5.02	0.43	0.85	10 S PC, BS Bas
Blue-Chip Paintings	-4.20	3.30	31.59	2.68	0.04	0.15	5 BS PC, BS Bas
Blue-Chip Paintings	-3.33	3.34	30.27	3.02	0.18	0.47	5 S PC, S Bas
Blue-Chip Paintings	-4.44	3.33	29.95	3.02	0.02	0.05	5 S PC, BS Bas
Blue-Chip Paintings	-4.12	3.24	30.86	3.38	0.12	0.38	10 BS PC, BS Bas
Blue-Chip Paintings	-3.23	3.32	31.59	3.17	0.14	0.56	10 S PC, S Bas
Blue-Chip Paintings	-4.37	3.27	31.19	3.17	0.12	0.47	10 S PC, BS Bas
Blue-Chip Classic Cars	-5.09	4.90	23.76	1.31	0.18	0.32	5 BS PC, BS Bas
Blue-Chip Classic Cars	-1.44	5.05	21.08	2.77	0.20	0.57	5 S PC, S Bas
Blue-Chip Classic Cars	-2.96	4.89	23.92	2.77	0.02	0.05	5 S PC, BS Bas
Blue-Chip Classic Cars	-3.68	4.89	24.40	1.53	0.31	0.62	10 BS PC, BS Bas
Blue-Chip Classic Cars	-1.01	5.10	24.04	3.08	0.15	0.62	10 S PC, S Bas
Blue-Chip Classic Cars	-2.70	4.92	23.05	3.08	0.13	0.54	10 S PC, BS Bas
Quarterly USD (Q1 1998 – Q3 2018)							
Global Art	2.06	2.32	20.77	0.26	0.22	0.53	5 BS PC, BS Bas
Global Art	6.16	2.88	19.32	0.38	1.28	4.29	5 S PC, S Bas
Global Art	4.43	2.32	20.56	0.38	0.12	0.40	5 S PC, BS Bas
Global Art	3.22	2.32	20.85	0.28	0.19	0.74	10 BS PC, BS Bas
Global Art	6.17	2.98	20.89	0.41	0.78	3.87	10 S PC, S Bas
Global Art	2.90	2.33	20.90	0.41	0.12	0.62	10 S PC, BS Bas
Global Paintings	5.82	0.85	3.93	0.99	0.14	0.37	5 BS PC, BS Bas
Global Paintings	7.31	1.74	3.70	1.48	0.30	0.64	5 S PC, S Bas
Global Paintings	4.62	0.83	3.88	1.99	0.21	0.47	5 S PC, BS Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
Global Paintings	7.08	0.81	3.10	1.68	0.17	0.64	10 BS PC, BS Bas
Global Paintings	6.77	1.83	4.37	1.61	0.21	0.66	10 S PC, S Bas
Global Paintings	5.19	0.83	4.16	2.06	0.21	0.71	10 S PC, BS Bas
Global Prints	3.51	0.86	4.37	1.00	0.03	0.14	5 BS PC, BS Bas
Global Prints	5.82	1.58	3.22	2.06	0.23	0.48	5 S PC, S Bas
Global Prints	4.78	0.81	4.17	2.25	0.28	0.56	5 S PC, BS Bas
Global Prints	4.96	0.81	4.23	1.02	0.05	0.32	10 BS PC, BS Bas
Global Prints	6.01	1.54	3.55	3.02	0.26	0.60	10 S PC, S Bas
Global Prints	3.76	0.77	3.75	2.48	0.36	0.77	10 S PC, BS Bas
Global Sculptures	5.89	0.98	5.34	1.09	0.07	0.26	5 BS PC, BS Bas
Global Sculptures	7.11	1.73	4.08	1.94	0.23	0.47	5 S PC, S Bas
Global Sculptures	3.34	0.92	5.26	1.12	0.05	0.21	5 S PC, BS Bas
Global Sculptures	3.37	0.93	4.93	1.10	0.06	0.36	10 BS PC, BS Bas
Global Sculptures	6.12	1.66	5.02	2.22	0.17	0.55	10 S PC, S Bas
Global Sculptures	4.37	0.93	6.21	1.12	0.06	0.51	10 S PC, BS Bas
Global Photographs	4.08	1.84	11.50	1.11	0.05	0.19	5 BS PC, BS Bas
Global Photographs	6.21	2.35	11.72	1.12	0.31	1.38	5 S PC, S Bas
Global Photographs	4.25	1.88	11.77	1.12	0.05	0.23	5 S PC, BS Bas
Global Photographs	5.33	1.89	11.26	1.12	0.06	0.37	10 BS PC, BS Bas
Global Photographs	5.92	2.41	12.38	1.14	0.21	1.52	10 S PC, S Bas
Global Photographs	4.85	1.87	12.40	1.14	0.07	0.51	10 S PC, BS Bas
Global Drawings	3.10	2.01	11.35	1.05	0.15	0.37	5 BS PC, BS Bas
Global Drawings	4.31	2.51	11.21	0.97	0.40	1.52	5 S PC, S Bas
Global Drawings	2.44	1.99	11.39	0.97	0.09	0.34	5 S PC, BS Bas
Global Drawings	4.02	2.01	10.98	1.06	0.12	0.49	10 BS PC, BS Bas
Global Drawings	4.25	2.58	12.06	0.97	0.27	1.80	10 S PC, S Bas
Global Drawings	2.96	1.99	12.09	0.97	0.09	0.57	10 S PC, BS Bas
Global Old Masters Art	6.50	1.44	12.27	0.59	0.10	0.33	5 BS PC, BS Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
Global Old Masters Art	8.58	2.12	11.40	0.60	0.76	2.85	5 S PC, S Bas
Global Old Masters Art	8.31	1.41	12.03	0.60	0.05	0.18	5 S PC, BS Bas
Global Old Masters Art	6.68	1.43	12.28	0.63	0.10	0.47	10 BS PC, BS Bas
Global Old Masters Art	8.73	2.21	12.54	0.60	0.50	3.26	10 S PC, S Bas
Global Old Masters Art	6.49	1.41	12.36	0.60	0.07	0.46	10 S PC, BS Bas
Global 19th C. Art	6.69	1.30	6.77	0.98	0.08	0.28	5 BS PC, BS Bas
Global 19th C. Art	9.46	2.04	6.82	1.01	0.36	1.58	5 S PC, S Bas
Global 19th C. Art	7.38	1.28	7.14	1.01	0.06	0.24	5 S PC, BS Bas
Global 19th C. Art	6.40	1.30	6.71	1.00	0.06	0.35	10 BS PC, BS Bas
Global 19th C. Art	8.95	2.09	7.69	1.02	0.26	1.92	10 S PC, S Bas
Global 19th C. Art	7.31	1.28	7.66	1.02	0.07	0.47	10 S PC, BS Bas
Global Modern Art	6.28	0.86	4.15	0.88	0.14	0.36	5 BS PC, BS Bas
Global Modern Art	6.04	1.71	4.08	0.88	0.46	1.96	5 S PC, S Bas
Global Modern Art	6.27	0.84	4.64	1.76	0.18	0.44	5 S PC, BS Bas
Global Modern Art	9.99	0.80	3.68	1.52	0.18	0.62	10 BS PC, BS Bas
Global Modern Art	6.66	1.84	5.08	0.88	0.32	2.41	10 S PC, S Bas
Global Modern Art	4.12	0.85	5.13	0.88	0.07	0.51	10 S PC, BS Bas
Global Post-War Art	3.00	1.21	6.71	0.91	0.10	0.32	5 BS PC, BS Bas
Global Post-War Art	4.85	1.92	6.00	2.54	0.22	0.45	5 S PC, S Bas
Global Post-War Art	3.56	1.07	5.55	2.76	0.23	0.49	5 S PC, BS Bas
Global Post-War Art	7.10	1.12	6.08	1.96	0.17	0.63	10 BS PC, BS Bas
Global Post-War Art	4.69	1.87	7.10	2.71	0.17	0.57	10 S PC, S Bas
Global Post-War Art	3.15	1.08	6.52	2.92	0.20	0.68	10 S PC, BS Bas
Global Contemporary Art	1.52	1.85	11.84	1.01	0.08	0.27	5 BS PC, BS Bas
Global Contemporary Art	3.73	2.28	11.97	1.06	0.34	1.32	5 S PC, S Bas
Global Contemporary Art	2.31	1.89	12.20	1.06	0.04	0.14	5 S PC, BS Bas
Global Contemporary Art	2.76	1.89	12.11	1.09	0.09	0.45	10 BS PC, BS Bas
Global Contemporary Art	3.77	2.34	12.81	1.07	0.24	1.65	10 S PC, S Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
Global Contemporary Art	1.98	1.85	13.08	1.07	0.06	0.40	10 S PC, BS Bas
US Art	3.21	0.97	4.81	0.99	0.05	0.20	5 BS PC, BS Bas
US Art	5.59	1.74	4.44	1.02	0.36	1.60	5 S PC, S Bas
US Art	2.68	0.97	5.31	1.02	0.07	0.29	5 S PC, BS Bas
US Art	2.84	0.96	4.64	0.99	0.06	0.39	10 BS PC, BS Bas
US Art	4.96	1.86	5.62	1.02	0.25	1.99	10 S PC, S Bas
US Art	3.39	0.96	5.59	1.02	0.07	0.54	10 S PC, BS Bas
Liquid Wine	-0.95	2.25	16.15	1.74	0.09	0.31	5 BS PC, BS Bas
Liquid Wine	0.77	2.32	15.79	3.53	0.18	0.35	5 S PC, S Bas
Liquid Wine	3.02	2.14	16.70	3.65	0.29	0.60	5 S PC, BS Bas
Liquid Wine	-1.20	2.13	17.56	1.77	0.09	0.52	10 BS PC, BS Bas
Liquid Wine	2.46	2.26	15.84	4.41	0.46	0.71	10 S PC, S Bas
Liquid Wine	1.41	2.12	15.46	4.41	0.53	0.80	10 S PC, BS Bas
Average Artist Paintings	-5.82	1.36	5.13	1.29	0.41	1.00	5 BS PC, BS Bas
Average Artist Paintings	-2.93	3.21	3.56	2.33	0.38	0.89	5 S PC, S Bas
Average Artist Paintings	-3.16	1.97	4.68	2.20	0.36	0.86	5 S PC, BS Bas
Average Artist Paintings	-3.81	1.46	4.70	1.11	0.36	0.92	10 BS PC, BS Bas
Average Artist Paintings	-2.65	3.14	4.45	2.61	0.24	0.83	10 S PC, S Bas
Average Artist Paintings	-4.90	1.77	4.79	2.46	0.23	0.82	10 S PC, BS Bas
Popular Artist Paintings	-1.82	2.28	10.13	0.32	0.33	1.03	5 BS PC, BS Bas
Popular Artist Paintings	-0.52	3.41	8.32	0.24	2.17	4.55	5 S PC, S Bas
Popular Artist Paintings	-2.04	2.29	9.80	0.24	0.21	0.43	5 S PC, BS Bas
Popular Artist Paintings	0.74	2.30	7.68	3.43	0.21	0.93	10 BS PC, BS Bas
Popular Artist Paintings	0.21	3.52	9.81	0.24	1.45	4.84	10 S PC, S Bas
Popular Artist Paintings	-3.30	2.28	9.72	0.24	0.15	0.50	10 S PC, BS Bas
Popular Euro-American Sculptures	0.53	0.65	1.88	0.19	0.74	1.53	5 BS PC, BS Bas
Popular Euro-American Sculptures	1.90	2.43	1.44	0.05	11.77	25.37	5 S PC, S Bas
Popular Euro-American Sculptures	0.39	0.64	1.89	0.05	1.08	2.34	5 S PC, BS Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
Popular Euro-American Sculptures	0.17	0.64	1.91	0.20	0.43	1.40	10 BS PC, BS Bas
Popular Euro-American Sculptures	2.22	2.46	1.75	0.05	6.37	17.93	10 S PC, S Bas
Popular Euro-American Sculptures	-0.38	0.69	1.71	0.05	0.69	1.95	10 S PC, BS Bas
Jewelry	0.52	0.87	2.44	0.58	0.16	0.45	5 BS PC, BS Bas
Jewelry	3.63	2.08	2.09	0.54	0.88	2.11	5 S PC, S Bas
Jewelry	-0.29	0.86	2.63	0.54	0.17	0.40	5 S PC, BS Bas
Jewelry	5.67	0.90	1.22	1.29	0.24	0.78	10 BS PC, BS Bas
Jewelry	3.40	2.06	2.47	0.54	0.50	1.72	10 S PC, S Bas
Jewelry	1.36	0.85	2.48	0.54	0.15	0.53	10 S PC, BS Bas
Global Stamps	2.22	0.97	2.51	0.69	0.17	0.46	5 BS PC, BS Bas
Global Stamps	5.18	1.90	2.41	0.62	0.73	3.16	5 S PC, S Bas
Global Stamps	2.75	0.98	3.03	0.62	0.06	0.24	5 S PC, BS Bas
Global Stamps	7.85	1.01	1.09	1.66	0.21	0.76	10 BS PC, BS Bas
Global Stamps	4.81	2.04	3.04	0.62	0.46	3.41	10 S PC, S Bas
Global Stamps	2.31	0.98	3.22	0.62	0.07	0.55	10 S PC, BS Bas
English 18th C. Furniture	12.59	1.14	1.51	0.70	0.17	0.33	5 BS PC, BS Bas
English 18th C. Furniture	10.87	2.40	2.73	0.43	1.16	4.67	5 S PC, S Bas
English 18th C. Furniture	8.12	1.11	3.48	0.43	0.10	0.42	5 S PC, BS Bas
English 18th C. Furniture	11.94	1.03	0.93	0.71	0.19	0.43	10 BS PC, BS Bas
English 18th C. Furniture	10.50	2.53	3.35	0.43	0.71	4.40	10 S PC, S Bas
English 18th C. Furniture	8.65	1.07	3.35	0.43	0.11	0.67	10 S PC, BS Bas
Classic Cars	-3.75	1.26	2.33	0.62	0.55	0.74	5 BS PC, BS Bas
Classic Cars	-0.07	2.19	3.05	0.43	1.14	3.18	5 S PC, S Bas
Classic Cars	-1.54	1.25	4.05	0.43	0.07	0.20	5 S PC, BS Bas
Classic Cars	-2.25	1.25	1.93	1.36	0.33	0.87	10 BS PC, BS Bas
Classic Cars	0.07	2.29	3.87	0.43	0.74	3.52	10 S PC, S Bas
Classic Cars	-3.12	1.26	4.03	0.43	0.08	0.40	10 S PC, BS Bas
Euro-Eastern Rugs/Carpets	7.91	1.66	5.19	0.50	0.25	0.42	5 BS PC, BS Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
Euro-Eastern Rugs/Carpets	9.47	2.73	4.91	0.44	1.05	2.80	5 S PC, S Bas
Euro-Eastern Rugs/Carpets	6.50	1.67	6.46	0.44	0.06	0.17	5 S PC, BS Bas
Euro-Eastern Rugs/Carpets	6.85	1.67	5.50	0.52	0.18	0.51	10 BS PC, BS Bas
Euro-Eastern Rugs/Carpets	9.96	2.73	6.32	0.45	0.73	3.22	10 S PC, S Bas
Euro-Eastern Rugs/Carpets	7.81	1.67	6.50	0.45	0.07	0.33	10 S PC, BS Bas
English Coins	0.52	1.10	1.62	1.13	0.16	0.34	5 BS PC, BS Bas
English Coins	0.65	1.79	1.34	2.58	0.24	0.45	5 S PC, S Bas
English Coins	-1.95	1.00	1.04	2.73	0.22	0.39	5 S PC, BS Bas
English Coins	2.52	1.01	0.67	1.48	0.25	0.68	10 BS PC, BS Bas
English Coins	0.85	1.79	2.74	2.45	0.19	0.53	10 S PC, S Bas
English Coins	-0.62	1.04	2.46	2.48	0.27	0.70	10 S PC, BS Bas
Diamonds	8.08	0.92	4.98	1.76	0.27	0.61	5 BS PC, BS Bas
Diamonds	6.55	2.36	4.58	0.25	2.01	8.15	5 S PC, S Bas
Diamonds	5.29	0.88	6.07	0.25	0.06	0.24	5 S PC, BS Bas
Diamonds	2.40	0.88	6.09	0.24	0.19	0.78	10 BS PC, BS Bas
Diamonds	6.31	2.53	5.90	0.25	1.37	8.64	10 S PC, S Bas
Diamonds	2.96	0.88	6.16	0.25	0.11	0.69	10 S PC, BS Bas
Monthly USD (Feb 1988 - Dec 2017)							
Liquid Wine	-2.96	1.12	17.89	0.77	0.43	0.57	5 BS PC, BS Bas
Liquid Wine	-2.86	1.26	12.25	2.76	0.31	0.51	5 S PC, S Bas
Liquid Wine	-2.76	1.25	11.57	2.76	0.32	0.54	5 S PC, BS Bas
Liquid Wine	-1.22	1.11	16.31	0.93	0.37	0.68	10 BS PC, BS Bas
Liquid Wine	-1.97	1.22	14.17	2.46	0.29	0.64	10 S PC, S Bas
Liquid Wine	-1.95	1.20	14.48	2.46	0.32	0.72	10 S PC, BS Bas
Average Artist Paintings	-0.88	1.07	4.35	1.59	0.30	0.98	5 BS PC, BS Bas
Average Artist Paintings	-0.16	1.55	3.68	0.10	2.79	8.77	5 S PC, S Bas
Average Artist Paintings	-0.85	1.08	4.83	0.10	0.35	1.11	5 S PC, BS Bas
Average Artist Paintings	-3.74	1.12	2.96	1.68	0.24	0.86	10 BS PC, BS Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
Average Artist Paintings	0.27	1.57	3.55	0.10	1.71	4.89	10 S PC, S Bas
Average Artist Paintings	-2.23	1.08	4.77	0.10	0.35	1.00	10 S PC, BS Bas
Popular Artist Paintings	1.55	1.36	5.74	1.10	0.27	0.68	5 BS PC, BS Bas
Popular Artist Paintings	4.31	1.67	5.63	0.44	0.42	1.36	5 S PC, S Bas
Popular Artist Paintings	1.94	1.44	5.93	0.44	0.02	0.05	5 S PC, BS Bas
Popular Artist Paintings	1.83	1.37	5.32	0.46	0.15	0.44	10 BS PC, BS Bas
Popular Artist Paintings	4.69	1.68	5.85	0.44	0.28	1.42	10 S PC, S Bas
Popular Artist Paintings	2.00	1.44	6.70	0.44	0.15	0.78	10 S PC, BS Bas
Popular Euro-American Sculptures	1.27	0.38	1.24	0.11	0.58	1.19	5 BS PC, BS Bas
Popular Euro-American Sculptures	5.10	1.05	0.56	0.02	13.75	33.11	5 S PC, S Bas
Popular Euro-American Sculptures	3.05	0.38	1.21	0.02	1.30	3.12	5 S PC, BS Bas
Popular Euro-American Sculptures	2.39	0.37	1.34	0.05	0.89	1.41	10 BS PC, BS Bas
Popular Euro-American Sculptures	5.52	1.05	0.63	0.02	7.90	21.78	10 S PC, S Bas
Popular Euro-American Sculptures	3.05	0.38	1.20	0.02	0.89	2.45	10 S PC, BS Bas
Jewelry	0.70	0.43	1.34	0.42	0.27	0.64	5 BS PC, BS Bas
Jewelry	5.25	0.94	0.48	0.20	1.24	5.03	5 S PC, S Bas
Jewelry	3.53	0.45	1.28	0.20	0.08	0.31	5 S PC, BS Bas
Jewelry	1.86	0.44	1.40	0.56	0.30	0.90	10 BS PC, BS Bas
Jewelry	5.59	0.95	0.85	0.20	0.85	5.01	10 S PC, S Bas
Jewelry	1.78	0.45	1.35	0.20	0.16	0.92	10 S PC, BS Bas
Global Stamps	3.22	0.49	1.75	0.46	0.24	0.69	5 BS PC, BS Bas
Global Stamps	6.20	0.94	0.77	0.22	1.13	4.44	5 S PC, S Bas
Global Stamps	4.45	0.48	1.49	0.22	0.07	0.30	5 S PC, BS Bas
Global Stamps	2.86	0.47	1.47	0.53	0.25	0.71	10 BS PC, BS Bas
Global Stamps	6.53	0.95	1.14	0.22	0.77	4.57	10 S PC, S Bas
Global Stamps	2.72	0.50	1.64	0.22	0.15	0.89	10 S PC, BS Bas
English 18th C. Furniture	7.16	0.59	1.25	0.38	0.33	0.53	5 BS PC, BS Bas
English 18th C. Furniture	10.55	1.05	1.04	0.32	0.75	3.05	5 S PC, S Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
English 18th C. Furniture	7.56	0.61	1.51	0.32	0.05	0.22	5 S PC, BS Bas
English 18th C. Furniture	9.59	0.69	0.32	1.02	0.22	0.54	10 BS PC, BS Bas
English 18th C. Furniture	10.81	1.07	1.32	0.32	0.49	2.70	10 S PC, S Bas
English 18th C. Furniture	8.03	0.61	1.91	0.32	0.18	0.96	10 S PC, BS Bas
Classic Cars	-2.39	1.13	2.15	0.46	0.29	0.55	5 BS PC, BS Bas
Classic Cars	1.76	1.42	2.92	0.37	0.57	1.72	5 S PC, S Bas
Classic Cars	-0.38	1.14	3.37	0.37	0.03	0.10	5 S PC, BS Bas
Classic Cars	-1.71	1.15	1.79	1.59	0.48	0.97	10 BS PC, BS Bas
Classic Cars	2.26	1.43	3.07	0.39	0.36	1.48	10 S PC, S Bas
Classic Cars	0.06	1.17	3.98	0.39	0.17	0.71	10 S PC, BS Bas
Euro-Eastern Rugs/Carpets	5.28	0.92	5.58	0.14	0.34	1.18	5 BS PC, BS Bas
Euro-Eastern Rugs/Carpets	8.45	1.25	4.05	1.87	0.47	0.74	5 S PC, S Bas
Euro-Eastern Rugs/Carpets	7.13	0.97	3.82	1.87	0.54	0.85	5 S PC, BS Bas
Euro-Eastern Rugs/Carpets	7.22	0.92	5.65	0.14	0.23	1.37	10 BS PC, BS Bas
Euro-Eastern Rugs/Carpets	8.95	1.31	5.03	0.28	0.52	1.39	10 S PC, S Bas
Euro-Eastern Rugs/Carpets	6.54	0.93	5.40	0.28	0.31	0.83	10 S PC, BS Bas
English Coins	-0.41	0.68	1.63	0.23	0.15	0.35	5 BS PC, BS Bas
English Coins	3.63	0.96	0.32	1.71	0.46	0.75	5 S PC, S Bas
English Coins	0.50	0.63	0.24	1.71	0.38	0.63	5 S PC, BS Bas
English Coins	1.32	0.61	0.37	1.39	0.13	0.46	10 BS PC, BS Bas
English Coins	3.16	1.05	0.67	1.53	0.38	0.78	10 S PC, S Bas
English Coins	1.40	0.63	0.38	1.53	0.33	0.67	10 S PC, BS Bas

Table A6: Emotional Yield Estimates: All GBP Specifications

This table shows all of the estimated model specifications for the emotional yields of the GBP collectibles.

Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
Blue-Chip Wine	-0.11	2.39	13.39	3.61	0.08	0.11	5 BS PC, BS Bas
Blue-Chip Wine	0.24	2.14	11.87	6.17	0.10	0.16	5 S PC, S Bas
Blue-Chip Wine	-0.66	2.15	10.90	6.17	0.10	0.15	5 S PC, BS Bas
Blue-Chip Wine	0.47	2.34	16.65	4.87	0.17	0.48	10 BS PC, BS Bas
Blue-Chip Wine	0.93	2.27	18.30	5.30	0.04	0.19	10 S PC, S Bas
Blue-Chip Wine	-0.82	2.35	17.71	5.30	0.15	0.64	10 S PC, BS Bas
Blue-Chip British Stamps	-0.42	1.88	9.85	0.53	0.21	0.70	5 BS PC, BS Bas
Blue-Chip British Stamps	2.30	1.92	7.04	1.04	0.86	1.80	5 S PC, S Bas
Blue-Chip British Stamps	-1.46	1.98	8.76	1.04	0.05	0.11	5 S PC, BS Bas
Blue-Chip British Stamps	-0.54	1.87	6.21	6.89	0.25	0.91	10 BS PC, BS Bas
Blue-Chip British Stamps	2.82	1.94	8.97	1.25	0.48	1.01	10 S PC, S Bas
Blue-Chip British Stamps	-0.01	1.91	7.99	1.25	0.31	0.64	10 S PC, BS Bas
British Art	1.63	1.56	7.38	2.83	0.03	0.07	5 BS PC, BS Bas
British Art	2.36	1.53	8.93	3.31	0.14	0.60	5 S PC, S Bas
British Art	0.93	1.55	8.56	3.31	0.01	0.06	5 S PC, BS Bas
British Art	1.28	1.51	9.32	2.90	0.15	0.60	10 BS PC, BS Bas
British Art	2.83	1.54	10.77	3.35	0.12	0.84	10 S PC, S Bas
British Art	-0.40	1.57	9.63	3.35	0.12	0.86	10 S PC, BS Bas
Violins	1.37	2.33	21.58	1.58	0.31	0.82	5 BS PC, BS Bas
Violins	3.65	2.83	20.78	2.23	0.70	2.37	5 S PC, S Bas
Violins	1.24	2.34	20.98	2.23	0.32	1.07	5 S PC, BS Bas
Violins	0.66	2.32	22.71	1.62	0.21	0.95	10 BS PC, BS Bas
Violins	3.72	2.84	21.72	2.30	0.40	2.12	10 S PC, S Bas
Violins	0.53	2.31	20.98	2.30	0.21	1.12	10 S PC, BS Bas
US Coins	-2.99	4.87	20.57	2.06	0.25	0.76	5 BS PC, BS Bas
US Coins	0.44	5.18	17.80	2.67	0.22	0.42	5 S PC, S Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
US Coins	-2.35	4.74	19.82	2.67	0.03	0.06	5 S PC, BS Bas
US Coins	-1.96	4.82	14.76	6.47	0.25	0.70	10 BS PC, BS Bas
US Coins	0.26	5.04	21.16	2.77	0.18	0.57	10 S PC, S Bas
US Coins	-1.40	4.81	20.29	2.77	0.21	0.66	10 S PC, BS Bas
Blue-Chip Paintings	-4.52	3.31	29.46	4.34	0.14	0.28	5 BS PC, BS Bas
Blue-Chip Paintings	-2.74	3.37	30.41	8.99	0.18	0.48	5 S PC, S Bas
Blue-Chip Paintings	-3.72	3.35	30.12	3.49	0.03	0.05	5 S PC, BS Bas
Blue-Chip Paintings	-4.56	3.32	30.07	4.67	0.20	0.46	10 BS PC, BS Bas
Blue-Chip Paintings	-2.84	3.40	33.66	3.52	0.12	0.45	10 S PC, S Bas
Blue-Chip Paintings	-5.17	3.37	32.33	3.52	0.16	0.60	10 S PC, BS Bas
Blue-Chip Classic Cars	-3.78	5.93	5.63	12.47	0.21	0.54	5 BS PC, BS Bas
Blue-Chip Classic Cars	-2.25	6.21	18.80	4.06	0.05	0.17	5 S PC, S Bas
Blue-Chip Classic Cars	-3.35	6.14	18.32	4.06	0.02	0.08	5 S PC, BS Bas
Blue-Chip Classic Cars	-6.83	6.58	3.84	14.04	0.31	0.99	10 BS PC, BS Bas
Blue-Chip Classic Cars	-1.43	5.80	19.60	4.77	0.05	0.21	10 S PC, S Bas
Blue-Chip Classic Cars	-2.90	6.39	18.52	4.77	0.15	0.59	10 S PC, BS Bas
				Monthly GBP (Feb 1988 - Dec 2017)			
Liquid Wine	-3.00	0.95	12.87	0.20	0.31	0.71	5 BS PC, BS Bas
Liquid Wine	-0.66	1.17	7.34	0.14	2.08	4.08	5 S PC, S Bas
Liquid Wine	-3.56	0.93	14.00	0.14	0.39	0.76	5 S PC, BS Bas
Liquid Wine	-6.32	1.09	9.99	0.86	0.45	0.94	10 BS PC, BS Bas
Liquid Wine	0.08	1.16	10.04	3.20	0.18	0.86	10 S PC, S Bas
Liquid Wine	-4.03	0.94	11.92	3.20	0.19	0.88	10 S PC, BS Bas
Average Artist Paintings	-6.23	0.92	10.08	0.07	0.59	1.61	5 BS PC, BS Bas
Average Artist Paintings	0.05	1.29	7.39	0.25	1.32	2.71	5 S PC, S Bas
Average Artist Paintings	-3.58	0.90	10.36	0.25	0.38	0.78	5 S PC, BS Bas
Average Artist Paintings	-3.48	1.03	9.22	1.05	0.48	0.98	10 BS PC, BS Bas
Average Artist Paintings	-1.83	1.18	6.89	2.44	0.27	0.68	10 S PC, S Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
Average Artist Paintings	-3.83	1.05	7.83	2.44	0.26	0.66	10 S PC, BS Bas
Popular Artist Paintings	-1.89	1.35	10.33	0.07	0.66	1.70	5 BS PC, BS Bas
Popular Artist Paintings	3.69	1.61	8.06	0.30	1.19	1.90	5 S PC, S Bas
Popular Artist Paintings	-0.47	1.35	10.70	0.30	0.37	0.58	5 S PC, BS Bas
Popular Artist Paintings	-1.54	1.56	10.88	0.09	0.24	0.89	10 BS PC, BS Bas
Popular Artist Paintings	3.93	1.64	6.43	0.37	0.55	1.18	10 S PC, S Bas
Popular Artist Paintings	0.69	1.37	11.13	0.37	0.38	0.82	10 S PC, BS Bas
Popular Euro-American Sculptures	-1.08	0.52	8.11	0.03	1.56	2.45	5 BS PC, BS Bas
Popular Euro-American Sculptures	4.70	0.75	4.82	0.25	1.12	3.29	5 S PC, S Bas
Popular Euro-American Sculptures	2.06	0.51	8.87	0.25	0.07	0.21	5 S PC, BS Bas
Popular Euro-American Sculptures	1.92	0.58	9.20	0.03	0.40	1.66	10 BS PC, BS Bas
Popular Euro-American Sculptures	4.23	0.77	6.16	2.51	0.18	0.86	10 S PC, S Bas
Popular Euro-American Sculptures	0.89	0.49	7.20	2.51	0.16	0.77	10 S PC, BS Bas
Jewelry	-0.96	0.59	8.46	0.03	1.47	3.97	5 BS PC, BS Bas
Jewelry	5.07	0.93	5.59	0.15	2.10	4.62	5 S PC, S Bas
Jewelry	0.95	0.59	8.76	0.15	0.10	0.21	5 S PC, BS Bas
Jewelry	0.51	0.68	9.26	0.03	0.46	1.37	10 BS PC, BS Bas
Jewelry	4.68	0.85	6.41	3.12	0.16	0.75	10 S PC, S Bas
Jewelry	1.93	0.58	6.04	3.12	0.15	0.69	10 S PC, BS Bas
Global Stamps	-0.03	0.52	8.04	0.02	1.89	3.06	5 BS PC, BS Bas
Global Stamps	6.24	0.76	6.80	0.40	0.86	1.92	5 S PC, S Bas
Global Stamps	1.64	0.51	8.69	0.40	0.19	0.42	5 S PC, BS Bas
Global Stamps	1.33	0.58	9.18	0.02	0.73	1.33	10 BS PC, BS Bas
Global Stamps	5.66	0.75	6.73	2.03	0.19	0.68	10 S PC, S Bas
Global Stamps	2.97	0.49	6.58	2.03	0.17	0.63	10 S PC, BS Bas
English 18th C. Furniture	4.32	0.60	8.39	0.06	0.29	0.68	5 BS PC, BS Bas
English 18th C. Furniture	10.41	0.96	4.86	0.13	2.40	5.36	5 S PC, S Bas
English 18th C. Furniture	6.77	0.58	8.78	0.13	0.13	0.29	5 S PC, BS Bas

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Asset	Conv Yield (%)	Adj. SE	Res Vol Reduct (pps)	$\max\lvert\beta_{\text{test}}\rvert$	$\frac{\text{MAD}}{\max\lvert\beta_{\text{test}}\rvert}$	$\frac{\text{MAD}}{\overline{\lvert\beta\rvert}}$	**Spec**
English 18th C. Furniture	5.07	0.67	8.76	0.05	0.12	0.56	10 BS PC, BS Bas
English 18th C. Furniture	9.87	0.87	6.78	2.13	0.19	0.66	10 S PC, S Bas
English 18th C. Furniture	7.48	0.62	6.44	2.13	0.19	0.65	10 S PC, BS Bas
Classic Cars	-4.54	0.88	8.92	0.08	0.53	1.91	5 BS PC, BS Bas
Classic Cars	0.71	1.21	6.23	0.08	4.27	4.69	5 S PC, S Bas
Classic Cars	-2.79	0.87	9.60	0.08	0.71	0.78	5 S PC, BS Bas
Classic Cars	-1.65	0.99	8.24	0.95	0.55	0.97	10 BS PC, BS Bas
Classic Cars	1.19	1.15	7.53	2.70	0.23	0.80	10 S PC, S Bas
Classic Cars	-1.24	0.95	6.89	2.70	0.22	0.76	10 S PC, BS Bas
Euro-Eastern Rugs/Carpets	2.36	0.98	9.99	0.08	0.36	0.90	5 BS PC, BS Bas
Euro-Eastern Rugs/Carpets	7.97	1.25	7.04	0.31	0.92	2.54	5 S PC, S Bas
Euro-Eastern Rugs/Carpets	3.89	0.98	9.71	0.31	0.21	0.58	5 S PC, BS Bas
Euro-Eastern Rugs/Carpets	2.75	1.12	10.40	0.11	0.14	0.66	10 BS PC, BS Bas
Euro-Eastern Rugs/Carpets	8.99	1.13	6.02	5.05	0.16	0.66	10 S PC, S Bas
Euro-Eastern Rugs/Carpets	6.08	1.01	5.89	5.05	0.15	0.63	10 S PC, BS Bas
English Coins	-2.59	0.60	8.43	0.08	0.66	2.39	5 BS PC, BS Bas
English Coins	3.16	0.94	4.75	0.14	2.18	5.18	5 S PC, S Bas
English Coins	-0.34	0.60	8.96	0.14	0.17	0.41	5 S PC, BS Bas
English Coins	-1.12	0.69	9.19	0.08	0.23	1.35	10 BS PC, BS Bas
English Coins	3.06	0.87	6.47	3.12	0.17	0.83	10 S PC, S Bas
English Coins	0.01	0.64	6.24	3.12	0.15	0.74	10 S PC, BS Bas

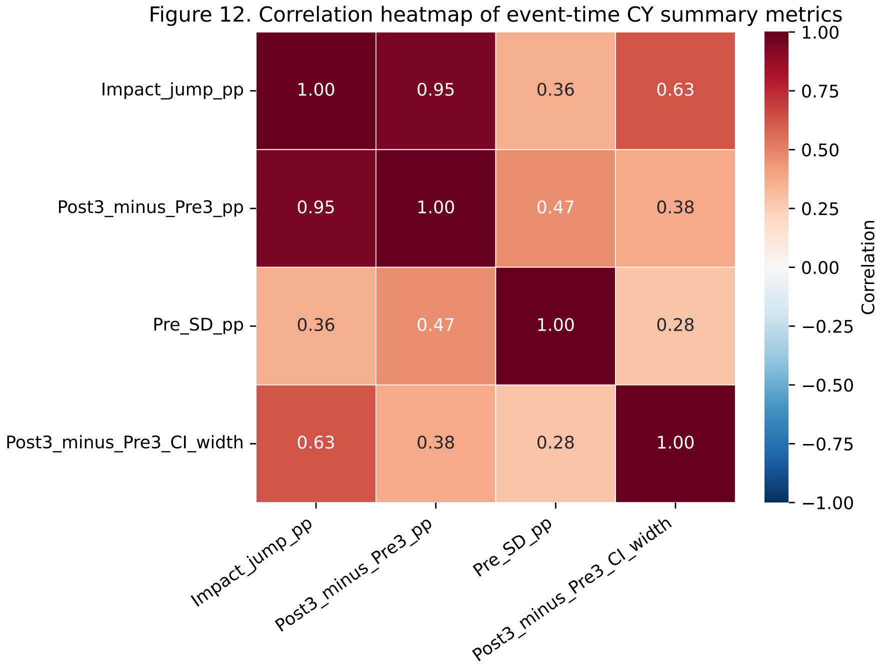

Figure A7: **Emotional yield correlation matrix across event times**

Notes: This figure shows how the main event-time diagnostics relate to each other across historical anchors (WWI 1914, Great Depression 1930, Oil/Inflation shock 1973, Global Financial Crisis 2008). It is a quick consistency check: do metrics that capture immediate and short-horizon changes move together, and are they linked to volatility or uncertainty?

Impact jump (pp): $\mathrm{CY}_0 - \frac{1}{3}\sum_{k\in\{-3,-2,-1\}} \mathrm{CY}_k$. *Interpretation:* change in emotional yield on impact (event year).

3-yr post − pre (pp): $\frac{1}{3}\sum_{k\in\{0,1,2\}} \mathrm{CY}_k - \frac{1}{3}\sum_{k\in\{-3,-2,-1\}} \mathrm{CY}_k$. *Interpretation:* whether the change persists over the next three years.

Pre-window SD (pp): $\mathrm{SD}\big(\{\mathrm{CY}_k : k \in \{-3,-2,-1\}\}\big)$. *Interpretation:* baseline dispersion across collectibles before the shock.

CI width (pp): Bootstrap 95% confidence-interval width for the *3-yr post − pre* difference. *Interpretation:* uncertainty around the short-horizon effect.

These correlations confirm that the episodic spikes seen in Figures 13–14 are internally consistent across metrics, but they do not indicate permanent factor loadings—effects are temporary and revert.

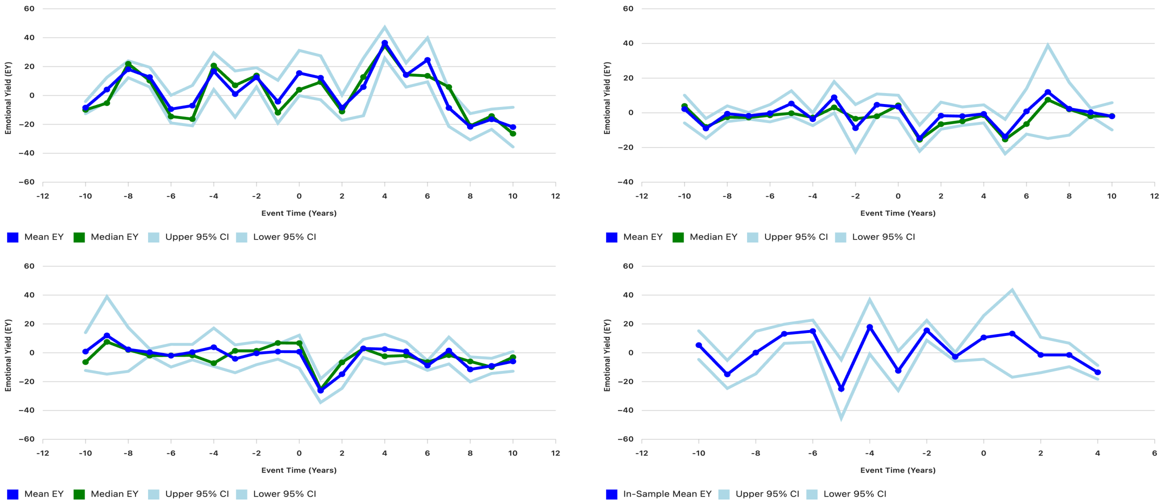

Figure A8: **Event-time EY (mean, balanced, median, and $N(k)$) around 1973, 1914, 1930 and 2008.**

Notes: Event-time emotional yield (EY) around major macro shocks (WWI, Great Depression, 1973 oil/inflation shock, 2008 financial crisis). Shaded band indicates pre-event window (k = 3. . . 1)

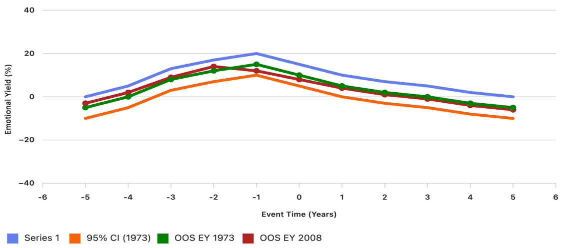

Figure A9: **Event-time EY using rolling-origin out-of-sample $\beta \cdot PC$ around 1973 and 2008.**

Notes: Event-time emotional yield (EY) using rolling-origin out-of-sample ·PC estimates around the 1973 oil/inflation shock and the 2008 financial crisis. EY rises sharply post-event (+15 pp for 1973; +14 pp for 2008), suggesting non-pecuniary demand intensifies during macro stress; confidence intervals widen near the event, reflecting estimation uncertainty.

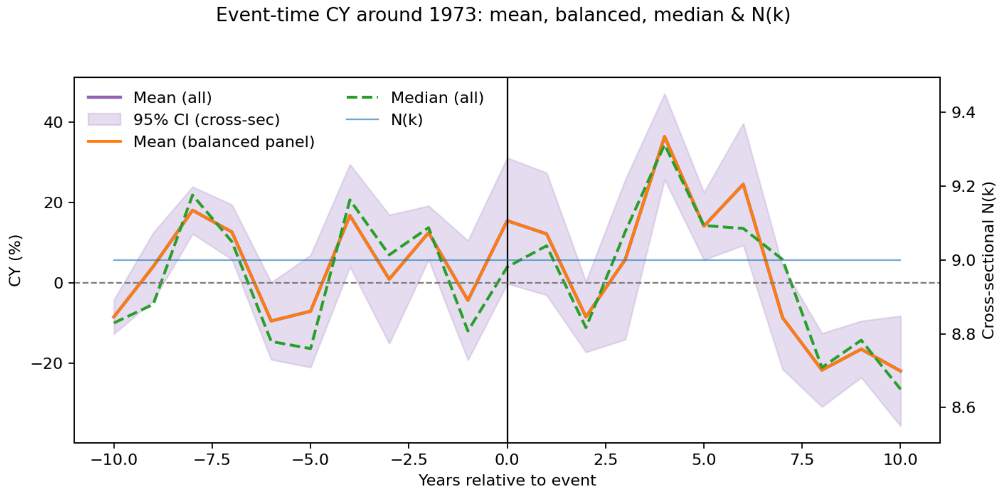

Figure A10: **Event–time EY around canonical episodes. Cross–collectible average EY in event time ($k = -10$ to $+10$) after removing traded risk via the FMP. Shaded band indicates the pre window $k \in \{-3, -2, -1\}$.**

Notes: Event-year jump and short-horizon post–pre differences in EY (percentage points) computed on cross-collectible averages; HAC z-statistics and bootstrap CIs reported.

Table A7: Illustrative Mid-Tier Artwork Rental Yields (Annualized, % of Fair Market Value.)

Provider / Source	Artwork Tier (FMV)	Typical Term	Advertised Yield (p.a.)
Artemus (illustrative)	\$20,000–\$50,000	6–12 months	3–5%
Teichert (illustrative)	\$10,000–\$25,000	6–12 months	2–4%
Corporate rental program A	\$5,000–\$15,000	6–12 months	4–6%
Corporate rental program B	\$15,000–\$30,000	3–6 months	5–8%

Notes: Yields are annualized fees as a percentage of the provider's fair-market value estimate and exclude platform margins, insurance, and logistics. Entries are illustrative and used only to scope magnitudes; not used in estimation. It reports illustrative rental yield ranges for mid-tier artworks (e.g., \$5k–\$50k tiers), expressed as annualized fees as a percentage of fair-market value, with examples labeled "Artemus (illustrative), Teichert (illustrative), Corporate rental program A/B." It is not used in estimation; it's a scope clarifier showing market-quoted magnitudes for monetized display rights. The table explicitly notes it excludes platform margins, insurance, and logistics and is illustrative only.

Table A8: Cost Sensitivity: Annualized Add-ons from Round-Trip Costs over Holding Horizons.

	Holding Period H (years)			
Panel A. Simple annualization c/H (percentage points per year)				
$c = 20\%$	0.71	0.63	0.56	0.50
$c = 25\%$	0.89	0.78	0.69	0.63
$c = 30\%$	1.07	0.94	0.83	0.75
Panel B. Log-return penalty $-\ln(1-c)/H$ (percentage points per year)				
$c = 20\%$	0.80	0.70	0.64	0.58
$c = 25\%$	1.01	0.88	0.79	0.72
$c = 30\%$	1.27	1.11	1.02	0.92

Notes: Panel A reports the back-of-the-envelope annualization c/H. Panel B reports the annualized log-return penalty $-\ln(1-c)/H$. Literature ranges for round-trip costs $c \in [20\%, 30\%]$ and average holding horizons $H \in [28, 40]$ are drawn from Campbell (2008), Dimson & Spaenjers (2011), Kraussl & Nasser Eddine (2018), Mei & Moses (2002), and Reitlinger (1961). Adding these magnitudes to the reported wedge $\overline{R^{FMP} - R^{C}}$ increases the economic shortfall. We do not re-estimate; these are scope-calibrations.

Table A9: Headline Means of Emotional Yields with Cost Add-ons (Back-of-the-Envelope.)

	Baseline Mean	+0.5 p.p.	+1.1 p.p.
Overall (Table 4)	2.64%	3.14%	3.74%
Public (USD, Q)	2.28%	2.78%	3.38%
Specialist (USD, Q)	0.45%	0.95%	1.55%
Private (USD, Q)	9.55%	10.05%	10.65%

Notes: Add-on range 0.5–1.1 p.p./year corresponds to c/H from Table A8. 0.5 is the min and 1.1 is the max from the table. Figures are illustrative back-of-the-envelope adjustments; we do not re-estimate. Emotional yield is defined as the residual return difference between a collectible and its factor-matched portfolio (FMP). Reported EY is the difference between the returns of FMP and the returns of collectibles. The collectible's true economic shortfall also includes annualized transaction/holding costs because the FMP is liquid and incurs negligible costs, and collectibles have high round-trip costs (auction premiums, seller commissions) and long holding periods.

Table A10: Event-time EY effects: event-year and short-horizon differences relative to pre-event baseline (percentage points). The event-year jump $\Delta(k=0)-$pre and the short-horizon difference $(0..+2)-(-3..-1)$ are computed on the cross-collectible average EY.

Event	$\Delta(k=0)-$pre	$(0..+2)-(-3..-1)$	z[event]	z[post]	Boot CI (post-pre)	N_{bal}
1914	3.77	-5.84	0.32	-0.49	[-13.10, 0.57]	9
1930	-0.69	-12.22	-0.04	-0.65	[-20.58, -3.70]	9
1973	11.90	3.38	0.64	0.18	[-13.54, 20.60]	9
2008	9.79	7.21	0.46	0.34	[-1.10, 14.76]	9

Notes: Event-time patterns are asymmetric across episodes: EY falls sharply and significantly around the Great Depression (post–pre 12.22pp; 95% CI [20.58, 3.70]), indicating a collapse in non-pecuniary demand during deflationary stress. In contrast, EY spikes around 1973 and 2008, but the short-horizon post–pre differences are not statistically different from zero (CIs include 0), consistent with transient, state-dependent amplification of emotional demand in inflationary/financial stress that reverses rather than persists; WWI shows a small, imprecise uptick.

Table A11: Subsample sensitivity: HAC $p < 0.10$ hit-rates and median coefficient sign by regressor.

Breakpoint	Top1 hit-rate	Top1 sign	War hit-rate	War sign	Rec hit-rate	Rec sign	ExpInfl hit-rate	ExpInfl sign
WWII	0.33	−	0.33	−	0.39	+	0.11	−
1973	0.22	−	0.39	−	0.39	+	0.11	−
1982	0.33	−	0.39	−	0.39	+	0.11	−
1990	0.11	−	0.44	−	0.11	−	−−−	−−−

Notes: Subsample sensitivity: HAC $p < 0.10$ hit rates and median coefficient sign by regressor across historical breakpoints (WWII, 1973, 1982, 1990). Signs indicate direction of EY response to Top1 share, war risk, recession share, and expected inflation. Top1 hit-rate shows The proportion of collectible assets for which the coefficient on the *Top 1% income share* (a proxy for wealth concentration) is statistically significant at the 10% level in asset-level regressions of EY. Computed as:

$$\text{Hit-rate} = \frac{\text{Number of assets with } p < 0.10}{\text{Total number of assets in subsample}}$$

Top1 sign is the median sign (positive or negative) of the coefficient on Top 1% income share across all assets in the subsample. War hit-rate is the proportion of assets for which the *war/political instability dummy* (e.g., WWI/WWII indicator) is statistically significant at the 10% level in EY regressions. War sign presents the median sign of the war dummy coefficient across assets. Rec hit-rate shows the proportion of assets for which the *recession share* (fraction of months in recession per year) is statistically significant at the 10% level. Rec sign shows the median sign of the recession coefficient across assets. ExpInfl hit-rate presents the proportion of assets for which *expected inflation* (e.g., one-year ahead inflation expectations) is statistically significant at the 10% level. ExpInfl sign shows the median sign of the expected inflation coefficient across assets. These metrics help assess whether emotional yields systematically respond to macroeconomic or speculative factors across different collectible categories and historical subsamples.

Table A12: Conditional EY means in recessions vs. expansions with NW–HAC difference tests.

Asset	N	Mean EY (Rec) %	Mean EY (Exp) %	Rec−Exp (pp)	p (HAC)
Wine (ACT, USD)	113	-2.52	1.79	-4.31	0.26
Wine (L1, USD)	113	-1.58	1.13	-2.71	0.53
Stamps (NOM, USD)	113	-1.15	0.82	-1.97	0.43
Stamps (ACT, USD)	113	-1.30	0.92	-2.22	0.41
Stamps (L1, USD)	113	-0.32	0.23	-0.55	0.85
Art (ACT, USD)	113	-1.39	0.99	-2.37	0.40
Art (L1, USD)	113	-0.58	0.41	-0.99	0.74
Violin 1 (USD)	113	1.42	-1.01	2.42	0.65
Violin 2 (USD)	113	-0.28	0.20	-0.48	0.93

Notes: Conditional EY means in recessions vs. expansions with HAC difference tests. Columns report mean EY (%) in each state, the recession–expansion difference (pp), and HAC p-values.

Table A13: Interactions: EY on War_Index, Recession, and War×Recession (HAC).

Asset	War coef. (p)	Recession coef. (p)	War×Rec (p)	R^2
Wine (ACT, USD)	-63.09 (0.30)	-17.27 (0.12)	123.15 (0.28)	0.02
Wine (L1, USD)	-74.29 (0.26)	-21.49 (0.08)	179.45 (0.15)	0.02
Stamps (NOM, USD)	-94.68 (**0.01**)	-7.65 (0.18)	50.65 (0.26)	0.03
Stamps (ACT, USD)	-103.25 (**0.01**)	-8.51 (0.16)	56.12 (0.23)	0.04
Stamps (L1, USD)	-114.80 (**0.01**)	-12.67 (**0.07**)	112.44 (**0.08**)	0.02
Art (ACT, USD)	-11.55 (0.78)	1.09 (0.88)	-34.31 (0.57)	0.01
Art (L1, USD)	-16.88 (0.70)	-2.13 (0.74)	10.27 (0.85)	0.00
Violin 1 (USD)	-82.47 (0.21)	3.46 (0.79)	-14.26 (0.91)	0.01
Violin 2 (USD)	-83.88 (0.25)	-6.73 (0.63)	56.75 (0.65)	0.01

Notes: Asset-level regressions of EY on war index, recession dummy, and War×Recession interaction. HAC p-values shown; coefficients indicate sign patterns of state dependence once traded risk is removed.

Table A14: Rolling-origin out-of-sample diagnostics by asset (sorted by R^2_{OOS}, best to worst). The OOS R^2 is against mean-demeaned actuals. Corr is the out-of-sample correlation between actuals and the predicted financial component. EY statistics summarize the OOS residual (Actual − Financial_OOS).

Asset	N_{OOS}	R^2_{OOS}	Corr(Act, Fin)	Mean EY_OOS (%)	SD EY_OOS (%)	%EY>0	Avg. SelComp
Wine (ACT, USD)	83	-0.01	0.29	0.72	27.28	51	1.72
Wine (L1, USD)	83	-0.03	0.27	-1.63	28.59	49	1.31
Art (ACT, USD)	83	-0.04	0.43	0.03	18.02	46	2.00
Art (L1, USD)	83	-0.08	0.45	-0.41	18.12	48	1.72
Stamps (NOM, USD)	83	-0.09	0.33	-1.09	17.94	48	2.00
Stamps (ACT, USD)	83	-0.09	0.34	-0.79	18.84	45	1.92
Stamps (L1, USD)	83	-0.15	0.33	-1.72	19.09	45	1.49
Violin 1 (USD)	83	-0.18	0.05	0.59	33.87	51	1.17
Violin 2 (USD)	83	-0.18	0.17	0.14	32.54	51	1.29

Notes: Rolling-origin out-of-sample diagnostics by asset. OOS R^2, correlation between actual returns and predicted financial component, and EY residual statistics (mean, SD, share >0) confirm estimator parsimony and absence of overfit.

Table A15: Estimator/span robustness around the PC set: effect of CV folds, max components, and standardization in PLS. Mean EY (HAC SE) from cv10/max10 std=1; R^2 and selected components (Comps) shown for four anchor specs.

	Mean EY	HAC SE	cv5/max5			cv10/max10			
Asset	(%)	(%)	R^2 std=1	R^2 std=0	ΔR^2	R^2 std=1	R^2 std=0	ΔR^2	Comps (std1 / std0)
Art (ACT, USD)	0.00	1.34	0.275	0.085	0.190	0.275	0.072	0.203	1 / 2
Art (L1, USD)	-0.00	1.33	0.263	0.056	0.207	0.263	0.073	0.189	1 / 2
Stamps (ACT, USD)	-0.00	1.49	0.242	0.071	0.170	0.242	0.051	0.191	1 / 2
Stamps (L1, USD)	0.00	1.59	0.203	0.066	0.137	0.203	0.049	0.155	1 / 2
Stamps (NOM, USD)	-0.00	1.39	0.246	0.070	0.176	0.246	0.050	0.196	1 / 2
Violin 1 (USD)	-0.00	1.77	0.122	0.036	0.086	0.122	0.036	0.086	1 / 2
Violin 2 (USD)	-0.00	1.82	0.140	0.041	0.099	0.140	0.041	0.099	1 / 2
Wine (ACT, USD)	0.00	2.02	0.272	0.104	0.167	0.272	0.104	0.167	1 / 2
Wine (L1, USD)	-0.00	2.15	0.254	0.102	0.153	0.254	0.102	0.153	1 / 2
Across-asset mean					**0.154**			**0.160**	

Notes. "std" indicates whether PLS regressors were standardized. ΔR^2 is std=1 minus std=0 within the same fold/max setting. "Comps" shows the selected components under cv10/max10 for std=1 vs std=0. and author computations in `OA_ROB4_alt_span_summary.csv`. Effect of CV folds (5 vs. 10), max PLS components (5 vs. 10), and scaling (standardized vs. raw). Mean EY (HAC SE), R^2, and selected components are shown; results are stable under standardization. Source: `alt_factor_span_specs.csv`.

Table A16: Block-bootstrap inference for mean EY (%): B = 2,000 **moving-block replications under block length** $L \in \{5, 10\}$**; series with** $N \geq 40$ **annual observations.**

Asset	N	Block L	Boot SE	2.5%	97.5%
Wine (ACT, USD)	113	5	2.06	-3.82	4.23
		10	1.85	-3.43	3.91
Wine (L1, USD)	113	5	2.23	-4.07	4.06
		10	1.92	-3.76	3.78
Stamps (ACT, USD)	113	5	1.38	-2.61	2.75
		10	1.02	-2.80	3.28
Stamps (L1, USD)	113	5	1.24	-3.26	3.58
		10	1.06	-2.80	3.28
Art (ACT, USD)	113	5	1.34	-2.59	2.74
		10	1.02	-2.80	3.28
Violin 1 (USD)	113	5	1.77	-3.22	3.58
		10	1.49	-2.79	3.28

Notes. See Section C1 for the detail methodology. Block-bootstrap inference for mean EY (%): $B = 2{,}000$ moving-block replications under block lengths $L \in \{5, 10\}$. Columns report bootstrap SE and 95% percentile confidence intervals; results align with HAC estimates.

Table A17: Event–time EY around canonical episodes (cross–collectible averages, pp.)

Anchor (year)	$\Delta_{k=0} - \overline{\text{pre}}$	$\overline{0..+2} - \overline{-3..-1}$	Peak within ± 2	Notes
WWI (1914)	$\approx +3.8$	(small)	(small)	Modest uptick; volatile, quick reversal
Great Depression (1930)	≈ -0.7	≈ -12.2	Trough ≈ -26.3	Deflationary collapse episode
Oil/Inflation shock (1973)	$\approx +11.9$	$\approx +15.5$	Peak $\approx +15.5$	Inflationary/stress spike
Global Financial Crisis (2008)	$\approx +9.8$	$\approx +14.9$	Peak $\approx +14.9$	Financial stress spike

Notes: For each anchor, we compute the event–year jump ($k = 0$ minus the pre–event mean over $k \in \{-3, -2, -1\}$) and a short–horizon post–pre difference (mean over $k \in \{0, 1, 2\}$ minus mean over $k \in \{-3, -2, -1\}$) using cross–collectible average EY after removing traded risk via the FMP. Values are percentage points (pp). These statistics are descriptive and not intended as structural evidence. Event-time EY around canonical episodes (WWI, Great Depression, 1973 oil/inflation shock, 2008 financial crisis). Columns report event-year jump ($k = 0$ minus pre), short-horizon post–pre difference, and peak within ± 2 years (pp).

Table A18: PLS-only transparency: EY descriptives by series (short sample).

Series	N	Mean EY	SD EY	% EY>0
ART_RET_NOMGBP_ACT (in USD)	83	0.0267	18.0186	45.78
ART_RET_NOMGBP_L1 (in USD)	83	-0.4116	18.1158	48.19
RET_STAMPS_NOMGBP (in USD)	83	-1.0911	17.9448	48.19
RET_STAMPS_NOMGBP_ACT (in USD)	83	-0.7936	18.8379	44.58
RET_STAMPS_NOMGBP_L1 (in USD)	83	-1.7157	19.0908	44.58
RET_WINE_NOMGBP_ACT (in USD)	83	0.7163	27.2802	50.60
RET_WINE_NOMGBP_L1 (in USD)	83	-1.6288	28.5853	49.40
Violin1Peter_NomGBP (in USD)	83	0.5943	33.8663	50.60
Violin2_NomGBP (in USD)	83	0.1434	32.5384	50.60

Notes: This table reports summary statistics for emotional yield (EY) across collectible return series using partial least squares (PLS) only, without shrinkage comparators. It documents mean EY, standard deviation, and the proportion of positive EY values, clarifying model behavior under short-sample constraints and reinforcing the rationale for excluding lasso/ridge/elastic-net alternatives. EY series are taken as provided in the enclosed panel (1930–2012). We do not add ridge/lasso/elastic-net comparisons in this revision given short-T and overfitting risk; instead, we document PLS-only discipline via transparent EY descriptives, consistent with our response letter and the cited short-sample rationale.

Table A19: Sensitivity of Δ_{LA} to p_d, σ_e, and κ.

p_d	$\sigma_e = 3\%$	$\sigma_e = 4\%$	$\sigma_e = 5\%$
0.15	0.56%	0.75%	0.94%
0.20	0.75%	1.00%	1.25%
0.25	0.94%	1.25%	1.56%
0.30	1.13%	1.50%	1.88%

Notes: $\lambda = 2.25$, $\kappa = 1$. $\Delta_{\text{LA}} = (\lambda - 1)p_d\kappa\sigma_e$. Sensitivity of Δ_{LA} (downside-risk adjustment term) to p_d, σ_e, and κ. Values shown in annualized percentage points under $\lambda = 2.25$; illustrates magnitude of risk-aversion benefit omitted from baseline EY.

C1. Methodology: Block-bootstrap inference for the mean of annual EY

Goal. This section explains how we perform block bootstrap for Table 16. Our goal is to obtain small-sample, serial-dependence-robust standard errors and percentile confidence intervals (CIs) for the mean annual emotional yield (EY) for each collectible.

C1.1. Why a block bootstrap?

Annual EY series exhibit serial correlation (persistence/smoothing). The classic IID bootstrap (resampling single years) breaks the dependence and understates uncertainty. The *Moving-Block Bootstrap (MBB)* resamples contiguous blocks of the series so that the within-block dependence is preserved, delivering valid inference for dependent data under weak stationarity/ergodicity assumptions. This is a standard approach in time-series econometrics for means and other smooth functionals. *(See Künsch, 1989; Politis & Romano, 1994; Lahiri, 2003; Efron & Tibshirani, 1993.)*

C1.2. Step-by-step procedure

1. **Input.** For each asset j, we observe annual EY $\{y_t\}_{t=1}^{T}$ (where T is the number of years). Compute the sample mean

$$\bar{y} = \frac{1}{T}\sum_{t=1}^{T} y_t.$$

2. **Choose block lengths.** Use two fixed block lengths, $L \in \{5, 10\}$, to bracket plausible dependence horizons at an *annual* frequency (roughly one to two business-cycle lengths). Reporting both provides a transparent *sensitivity check.*[19]

3. **Form overlapping blocks.** Create the $T - L + 1$ overlapping blocks

$$B_1 = (y_1, \dots, y_L),\ B_2 = (y_2, \dots, y_{L+1}),\ \dots,\ B_{T-L+1} = (y_{T-L+1}, \dots, y_T).$$

4. **Resampling scheme (MBB).** For each replication $b = 1, \dots, B$ with $B = 2{,}000$:
   (a) Draw $K = \lceil T/L \rceil$ blocks with replacement from $\{1, \dots, T-L+1\}$.
   (b) Concatenate them to form $y^{*(b)}$ of length at least T.
   (c) Trim to the first T observations.
   (d) Compute $\bar{y}^{*(b)}$.

5. **Bootstrap SE and CI.** From $\{\bar{y}^{*(b)}\}_{b=1}^{B}$:

[19] Alternatives such as data-driven block-length selection (e.g., Politis & White, 2004) are viable; we prefer fixed L with a short sensitivity grid.

- **Bootstrap SE**: sample SD of $\bar{y}^{*(b)}$.
- **95% percentile CI**: empirical 2.5th and 97.5th percentiles.

6. **Reporting.** Report ($\bar{y}$, $\mathrm{SE}^{\mathrm{boot}}$, $\mathrm{CI}_{2.5}$, $\mathrm{CI}_{97.5}$) under $L = 5$ and $L = 10$ (TableA19). Omit assets with $T < 40$.

C1.3. Why this specific choice (and not something else)?

- **Versus HAC (Newey–West).** HAC is asymptotic; MBB is finite-sample and preserves dependence. We report both and find broadly similar uncertainty.
- **Versus IID bootstrap.** Ignores serial correlation and understates uncertainty.
- **Versus parametric (AR-sieve).** Requires correct model; we prefer nonparametric.
- **Versus stationary bootstrap.** Random-length blocks are fine; MBB is simpler and aligns with a fixed annual horizon; results were similar for both L values.

C1.4. Tuning, diagnostics, and replications.

- **Block lengths** $L = 5, 10$**:** Span low-frequency dependence at annual horizons.
- **Replications** $B = 2{,}000$**:** Stable percentile CIs in practice.
- **Seeds/reproducibility:** Fix RNG seed and log drawn block indices.