Colors of Growth*

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Abstract

We develop a novel approach to measuring long-run economic growth by exploiting systematic variation in the use of color in European paintings. Drawing inspiration from the literature on nighttime lights as a proxy for income, we extract hue, saturation, and brightness from pixels to construct annual indices for Great Britain, Holland, France, Italy, and Germany between 1600 and 1820. These indices track broad trends in existing GDP reconstructions while revealing higher-frequency fluctuations—such as those associated with wars, political instability, and climatic shocks—that traditional series smooth over. Our findings demonstrate that light, decomposed into color and brightness components, provides a credible and independent source of information on early modern economic activity.

JEL classification: O47, C55, Z11, N01, N13.

Keywords: Economic growth, colors, brightness, paintings, historical proxies.

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1 Introduction

How can we measure economic growth to understand when and where it took hold? Despite decades of extensive research, our understanding remains constrained by the scarcity and limitations of long-run data. Gross Domestic Product (GDP) reconstructions provide only coarse approximations.[1]

Recent economic studies, beginning with Henderson, Storeygard and Weil (2012), show that nighttime luminosity is a powerful proxy for contemporary economic activity because brightness captures variation in material prosperity and human production. We build on the same intuition in a historical setting, using paintings as visual records of past economic conditions. In this setting, brightness on the canvas is the closest analogue to luminosity-based proxies, while color composition provides additional information on pigments, techniques, and access to costly or technologically demanding inputs. Paintings thus encode both the intensity of light and the material conditions under which visual production took place. Exploiting this largely untapped source of information, we use color and brightness in historical paintings to construct a new proxy for economic activity across locations and over time.

In this paper, we argue that, for Europe between the seventeenth and early nineteenth centuries – the cradle of modern economic growth – the brightness and color composition of visual artifacts provide a novel source of information for measuring GDP. To do this, we specifically consider oil paintings, which combine this information with systematic data on material pigments and the diffusion of new technological conditions of their time. The cost of pigments varied substantially, depending on whether their production relied on locally available materials or on long-distance trade and technologically intensive processes. Consequently, their use captured both economic capacity and integration into global supply networks. By quantifying these color characteristics, we recover information about economic activity that traditional data sources may overlook.

[1] Among the numerous contributions, see the analyses of the limitations of different versions of the Penn World Table by Temple (1998), Deaton and Heston (2010), Johnson et al. (2013), and Feenstra, Inklaar and Timmer (2015). From a policy perspective, Stiglitz et al. (2009) criticizes the limitations of GDP as a measure of welfare for countries and individuals.

The core idea of the study is simple and directly tied to economic fundamentals: light is not only a useful indicator of growth, but its decomposition reveals even more information. The palette available to artists was constrained by resource abundance, technological progress, and market access, the key ingredients of economic development. As emphasized by color and science historians, chromatic choices in historical works reflect the availability of pigments, the diffusion of new technologies, and broader material conditions (see, *e.g.*, Ball, 2001 and Pastoureau, 2019). For example, whereas red pigments were historically abundant in nature and therefore inexpensive (Ball, 2001), intense ultramarine blue could, before 1700, be obtained only from lapis lazuli imported at considerable cost from Afghanistan (Gage, 1999). In Renaissance Italy, its use was restricted to the wealthiest civic and religious institutions, revealing both the extent of trade networks and the affluence of their patrons (Pastoureau, 2023a). Similarly, the same color can reveal different socioeconomic meanings depending on prevailing cultural conventions. For example, while yellow was long associated with treason and deceit, in the Netherlands it often denoted prestige and prosperity (Pastoureau, 2019). In addition, the introduction of printed cottons in the early seventeenth century coincided with Europe's "*Industrious Revolution*" (1600–1800), a period during which rising GDP per capita was driven more by consumer demand than by technological progress (De Vries, 2008). One of its most visible manifestations was a fascination with bright colors, particularly in printed textiles (Styles, 2007). This is also captured by the vivid tones in the paintings of Johannes Vermeer (1632–1675) — from the *Girl with a Pearl Earring* (1668) to *The Geographer* (1669) — reflect this growing chromatic richness, itself a symptom of evolving patterns of consumption and production.

Building on these insights, we develop a new framework for measuring long-run economic growth by quantifying the use of color and brightness in a large dataset of European paintings spanning several centuries, regions, and cities. We treat the color spectrum preserved in oil paintings between the 17th and 19th centuries as a quantifiable historical record of material conditions, allowing us to recover continuous, high-frequency information on economic activity where conventional data are absent. To do so, we decompose each painting using an "*econometric prism*": we extract systematic information on hue, saturation, and value (HSV, Smith, 1978) from millions of pixels and then apply

principal component analysis (PCA) to derive a summary index of brightness and chromatic composition from the first principal component. This approach offers two advantages: the HSV approach minimizes biases arising from human perception, while PCA provides a rigorous statistical summary of color features. We then relate this index to established measures of development such as urban population and income, thereby constructing a new proxy for economic activity that allows us to study growth dynamics where conventional data are sparse or uncertain.

We apply this approach to construct annual color-based economic indices for Great Britain, France, Italy, Germany, and Holland between 1600 and 1820. These indices closely track existing GDP reconstructions where available, supporting the validity of our method, while revealing short-run fluctuations that conventional series smooth over.

Our findings show that the color index corresponds with many current results regarding long run GDP estimates for individual countries. For example, it clearly documents the pronounced growth in Great Britain in the 17th century, the Golden Age in the Netherlands, the Thirty Years' War in Germany and the French Revolution. However, our index also allows us to better understand detailed nuances. We can measure detailed institutional effects in relation to parliamentary co-determination and growth in England in the 17th century. We also find a clear turning point after the Glorious Revolution in our color index, which is missing in other quantitative studies. We find a turning point for English industrialization shortly after 1780, but it is not as pronounced. Based on our color index, we also find phases of growth or stagnation that deviate from existing GDP estimates for Germany or France, for example, but are strongly consistent with historical narratives.

Moreover, the factor structure of our indices highlights systematic relationships between specific colors and economic conditions, consistent with insights from art and color history. Our results are robust to alternative specifications, including robust PCA and restrictions to indoor paintings only, ensuring that they are not driven by outliers or compositional biases in the dataset.

We further validate our results with two complementary exercises. First, a city-level regression analysis shows that colors derived from paintings is significantly associated with urban population, a conventional proxy for income

before the Industrial Revolution. Second, we address a potential criticism: the chromatic composition of paintings may not perfectly reflect real-world colors, either because artists deliberately altered palettes or because aging has changed the pigments' hues. Our results indicate that the extracted colors closely correspond to the paintings' original albedo and prevailing climatic conditions, consistent with evidence that painters sought naturalistic representation. An additional exercise using yearly grape sugar content in Germany, a proxy for solar radiation, provides a further robustness check on this relationship. Together, these exercises support the reliability of our color-based indices and reinforce the broader argument that color and light carry measurable socioeconomic significance across time and place.

Taken together, our analysis contributes to the literature on historical measurement and economic growth along three main dimensions. First, we propose a novel indicator for measuring long-run economic growth. The timing of the onset of sustained economic growth depends critically on measurement choices. Focusing first on Great Britain—the cradle of the Industrial Revolution—previous studies using GDP, capital, and labor reconstructions date this turning point around 1750 (Crafts and Harley, 1992), while population-based proxies imply earlier periods (Kremer, 1993 and Acemoglu, Johnson and Robinson, 2005). Other scholars have emphasized human capital dimensions such as nutrition and mortality (Fogel, 2004) or height (Steckel, 2009), and more recent work highlights how alternative productivity measures reshape historical narratives (Bouscasse, Nakamura and Steinsson, 2024). Our new color-based measure complements these approaches by offering an independent, high-frequency proxy when conventional data

Second, our methodology builds on the insight of Henderson, Storeygard and Weil (2012) that satellite-recorded nighttime lights provide a reliable proxy for modern economic activity (see the reviews in Donaldson and Storeygard, 2016 and Michalopoulos and Papaioannou, 2018). While this technique cannot be extended to pre-modern periods, the same principle applies: brightness reflects material prosperity. Our study therefore provides a pre-industrial analogue to the night-lights approach and complements a growing literature that extracts quantitative information from historical testimonies such as books, photographs, and visual art. For instance, Hills et al. (2019) trace historical well-being through textual analysis of published books; Voth and Yanagizawa-

Drott (2024) apply convolutional neural networks to 14 million yearbook photos to study cultural change; and Gorin, Heblich and Zylberberg (2025) analyze more than 600,000 paintings dating back to 1400 using machine learning to infer emotional content. Our contribution differs by moving beyond cultural or emotional interpretations of historical artifacts and instead using colors directly as a proxy for long-run economic growth. In doing so, we bridge the literature on alternative proxies for GDP with the emerging use of cultural data, showing that systematic information embedded in artistic works can be transformed into quantitative indices of economic activity.

Third, we provide the first quantitative analysis of the relationship between color composition and its economic, geographical, and temporal context. As discussed in Section 4, the PCA loadings not only confirm known symbolic meanings of colors as identified by color historians but also reveal systematic regional patterns that reflect local economic trajectories.

The remainder of the paper proceeds as follows. Section 2 documents the evolution of color and brightness in paintings across regions and time. Section 3 details our empirical methodology. Section 4 presents the color-based economic indices and validation exercises. Section 6 concludes.

2 Economic Growth, Brightness, and Color

Color in historical paintings contains information about underlying economic conditions, not because any individual color mechanically tracks growth, but because different dimensions of color capture distinct aspects of material life. Brightness is the closest visual analogue to luminosity-based proxies of economic activity and, more broadly, reflects the lighting and material environments in which artworks were produced. Hue and saturation, by contrast, capture additional variation in pigments, techniques, and access to costly or technologically demanding inputs. To separate these margins in a transparent way, we represent color in a hue-saturation-value (HSV) space, which distinguishes brightness from chromatic intensity and palette composition. HSV is widely used because it separates brightness from chroma in a way that is both intuitive and empirically convenient (Smith, 1978). In addition, this decomposition provides an economically interpretable framework for measuring color

and motivates the variables that form the building blocks of the country-level indices constructed later in this section.

2.1 Measuring Color in Paintings

Our first step is to convert each painting into a small set of objective visual features. We want these features to capture three aspects of the image that are central to our analysis: the overall brightness of the canvas, the intensity of the colors, and the dominant regions of the palette. These dimensions are naturally represented in hue–saturation–value (HSV) space, where value captures brightness, saturation captures chromatic intensity, and hue summarizes palette choice. Figure 1 illustrates this representation: hue varies around the circle, while saturation and value govern chromatic intensity and brightness.

Figure 1: HSV Colors



Note: The figure displays the 108-bin HSV (hue–saturation–value) color space used in our analysis. Hue is arranged around the circle in 12 equally spaced segments (red through rose in 30° steps). For each hue, saturation and value are discretized into three levels, shown as concentric rings: the innermost corresponds to the darkest, least saturated bins, while colors become progressively brighter and more saturated as one moves outward. Each cell in the grid defines one of the 108 color bins that enter our empirical analysis.

This measurement strategy echoes the logic of the night-lights literature. Just as nighttime luminosity provides a brightness-based proxy for modern economic activity (Henderson, Storeygard and Weil, 2012), brightness and chromatic composition in paintings can capture economically relevant variation in periods in which conventional data are scarce. An additional advantage

is that our procedure is fully automated and does not rely on training data or human labeling, which makes it transparent and replicable. Finally, focusing on the statistical distribution of colors rather than subjective interpretation is consistent with evidence from cognitive science, which shows that visual systems represent color ensembles through their distributional properties (*e.g.*, Chetverikov, Campana and Kristjánsson, 2017); this is more robust than context-dependent visual inference tasks such as facial emotion recognition (Barrett, 2017).

We therefore use HSV as a conceptual decomposition of color into brightness, chromatic intensity, and palette composition. Section 3.2 explains how we operationalize this representation by discretizing each painting into a fixed HSV histogram and aggregating these features over time.

2.2 Brightness (Value) and Economic Activity

Within the HSV representation, *value* captures brightness, that is, the luminance conveyed on the canvas. Of the three HSV channels, value has the most direct connection to the modern measurement literature. Most prominently, Henderson, Storeygard and Weil (2012) show that nighttime luminosity provides a useful proxy for contemporary economic activity when conventional statistics are incomplete. Related work links illumination more broadly to productivity and behavior: Nordhaus and Hulten (1997) studies the long-run evolution and prices of artificial lighting technologies as indicators of productivity, while Hirshleifer and Shumway (2003) documents a correlation between stock returns and sunny trading days. These results motivate treating brightness as a measurable correlate of material prosperity in historical settings as well.

In paintings, higher brightness is plausibly associated with several economically relevant conditions. Better access to artificial illumination, improved pigments, refined oils, and higher-quality grounds all make lighter tonal ranges more feasible. More generally, brighter interiors and lighter palettes may reflect production environments in which materials, techniques, and lighting conditions improve with wealth and technological progress. Historical evidence is consistent with this interpretation. Del Bo (2023) identifies strong correlations between artificial lighting and socio-economic dynamics in medieval Italy, while

Field (2003) highlights electricity as a major driver of modern growth. Art-historical studies (Schivelbusch, 1995; Homann, 2015; Karasoulas and Clayson, 2016; Clayson, 2019) likewise document that pictorial brightness and illumination evolved with the spread of gas and electric lighting.[2]

For our purposes, the key point is not that brightness causes growth, but that it may co-move with underlying material conditions in a systematic way. This makes the value channel the natural entry point for our analysis. In the historical period we study, brightness is the closest visual analogue to modern luminosity-based proxies and provides the most direct channel through which paintings may capture variation in economic activity.

2.3 Chromatic Composition: Saturation, Hue, and Material Constraints

Beyond brightness, the remaining two HSV channels capture chromatic composition. Saturation measures chromatic intensity, that is, how vivid or muted colors appear on the canvas. Hue measures palette composition, that is, which broad color families dominate a painting. Economically, these dimensions are informative because they capture different margins through which material conditions may shape visual production.

Saturation is informative about the intensity with which pigments are deployed. In historical paintings, highly saturated colors were often more difficult and more costly to produce, since they depended on the availability of strong pigments, the quality of binders and grounds, and the painter's ability to apply color-rich layers successfully. By contrast, muted tones are more compatible with cheaper materials, thinner application, or palettes constrained by limited access to high-quality inputs. In this sense, saturation captures an intensive margin of chromatic use. This channel is especially relevant before the large-scale industrial production of synthetic pigments, when vivid chromatic effects relied more heavily on costly materials and unevenly diffused production techniques (see, *e.g.*, Ball, 2001; Gage, 1999).

[2]Micro-level data on the diffusion of electricity are not available at the frequency required for direct testing in our historical setting.

Hue captures a different margin. It does not measure intensity, but the relative allocation of color across broad families. Different parts of the palette depended on different pigments, and pigment availability was shaped by geography, trade, and production technology. Shifts in hue composition can therefore reflect changes in market access, relative input costs, and the diffusion of new materials. Historians of color emphasize that some hues were relatively abundant and inexpensive, while others depended on long-distance trade, mineral extraction, or technologically demanding preparation (*e.g.*, Ball, 2001; Gage, 1999; Pastoureau, 2019).

For example, blue pigments historically relied on materials such as lapis lazuli, linking their use to trade networks and technological progress. In our data, colors in the blue range are also among those most consistently associated with larger urban populations in the cross-sectional regressions (Appendix C1), providing a simple illustration of how palette composition may reflect underlying economic conditions. More generally, our empirical approach does not rely on fixed symbolic meanings of individual colors; instead, it exploits the joint distribution of hue, saturation, and value as a statistical summary of visual production. A more detailed discussion of the historical evolution and symbolic meanings of individual colors is provided in Appendix E.

For our purposes, the main role of saturation and hue is to complement brightness. Two paintings may be equally bright but differ substantially in chromatic intensity or in palette composition. By separating these dimensions, HSV allows us to distinguish changes in luminance from changes in the intensity and composition of color. We therefore interpret saturation and hue as complementary channels through which material prosperity, market access, and production technology may become visible in artworks.

3 From Colors to Indices: Data and Measurement

This section describes the data and the procedure used to construct the color-based economic indices. We first define the painting sample, then show how the HSV representation introduced in Section 2 is translated into painting-level

measures and aggregated into annual series, and finally how these series are summarized using principal component analysis.

3.1 Painting Dataset

Our primary source is the Web Gallery of Art (WGA), a large curated database of European paintings with standardized metadata on artist, medium, date, location, and scene descriptors. We use WGA because these variables allow us to impose transparent *ex ante* sample restrictions and to construct color measures that are more comparable across works than those available from broader image repositories.[3]

The raw WGA corpus contains 32,112 objects. Because color is our primary signal and comparability in pigment behavior and surface reflectance is essential, we restrict attention to oil paintings on canvas or panel. We therefore exclude sketches, drawings, prints, frescoes, copper or enamel miniatures, photographs, and blank or monochrome studies that are unsuitable for HSV-based measurement.

We focus on the period 1565–1835, when coverage is relatively dense and oil-painting techniques are comparatively stable. Our main analysis centers on Great Britain, France, Germany, Italy, and Holland. We focus on Holland rather than the full Netherlands for consistency with the benchmark historical series used in Van Zanden and van Leeuwen (2011). Because exact work-level creation sites are not consistently available, we assign each painting to the country associated with the artist's death place, mapped to present-day borders. We interpret this as a transparent and comparable artist-level geographic attribution that captures the painter's late-career environment rather than the literal production site of each canvas, in the spirit of work that uses birth and death locations of historical creatives as person-level geographic markers rather than exact sites of production (Serafinelli and Tabellini, 2022).

The resulting working sample contains 10,382 paintings. Of these, 7,802 belong to the five core countries in the baseline analysis—Italy (2,655; 25.6%),

[3]The Web Gallery of Art is available at `https://www.wga.hu`. As an informal check on coverage, of the 90 artists contemporary with our period of analysis and identified by the art critic Roger de Piles (1635-1709) in Buckridge (1796) as representative of his time, only two are not included in our data.

Holland (2,573; 24.8%), France (1,617; 15.6%), Great Britain (588; 5.7%), and Germany (369; 3.6%).

3.2 Constructing Painting-Level HSV Features

Building on the conceptual decomposition introduced in Section 2, we represent each painting as a histogram in HSV space. In practice, we discretize HSV into a fixed "paint-by-numbers" palette of 108 bins. Hue is divided into 12 equally spaced slices, and within each slice saturation and value are each divided into three levels, yielding $12 \times 3 \times 3$ bins. After converting each image to HSV, we assign every pixel to one of these bins and summarize the painting by the shares of pixels in each bin. Because the shares sum to one, the resulting feature vector is invariant to file size and resolution. Figure 2 illustrates this mapping by showing, for several paintings, the histogram of the 20 most frequent bins.[4]

Figure 3 depicts how different regions of the color space correspond to distinct visual palettes, which we relate to economic conditions in the following subsections. We return to this point in Section 5, where we show that the resulting HSV-based measures are robust and externally valid proxies for environmental and economic conditions.

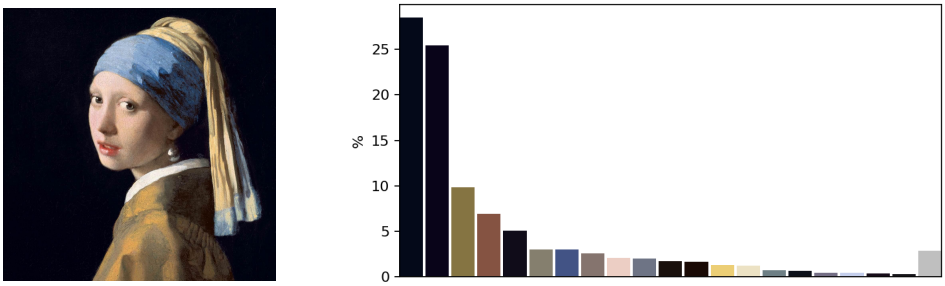
3.3 Constructing Color Time Series

Using the painting-level HSV histograms described in Section 2, we construct annual country-level series that summarize the evolution of color composition over time. While levels of color use already contain information about material conditions, changes in color use are especially informative for economic history because they capture shifts in technology, demand, and production constraints across painter cohorts. Shifts in artistic palettes rarely occur at random: they may reflect technological innovations (*e.g.*, the introduction of new pigments),

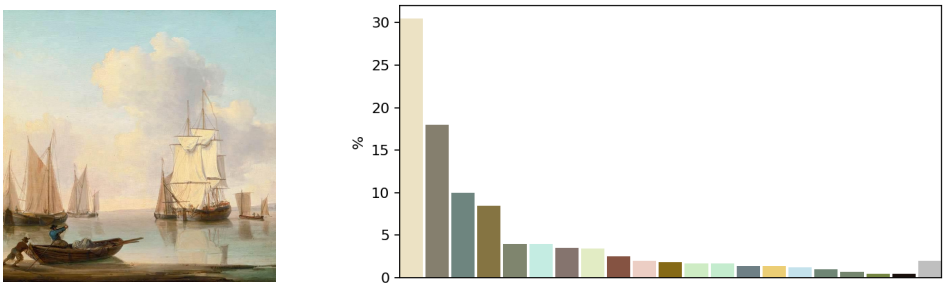
[4]Rare but visually extreme cases, such as unfinished works or experimental studies dominated by a single ground tone, can generate highly concentrated HSV histograms. To prevent such cases from disproportionately influencing aggregate statistics while retaining them in the sample, we restrict attention to pixels in the painted area (excluding uniform margins) and apply mild trimming by winsorizing the upper tail of the bin-share distribution (top 2%).

Figure 2: From Paintings to Color Histograms – Examples

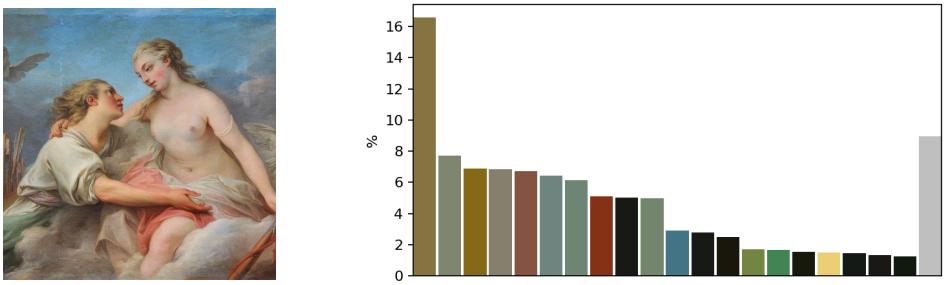
(a) Johannes Vermeer – Girl with a Pearl Earring



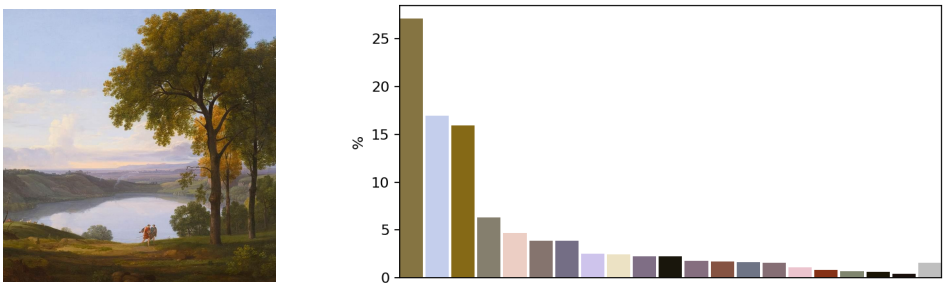
(b) William Anderson – Shipping in a Calm Sea off the Coast



(c) Clément Louis Marie Anne Belle – Venus and Adonis



(d) Nicolas-Didier Boguet – View of Lake Nemi



Note: For each painting, the right-hand panel reports the 20 most frequent colors from our 108-bin HSV (hue–saturation–value) histogram. Bars are ordered by relative frequency and their fill corresponds to the HSV center of each bin. The rightmost gray bar aggregates the residual share of the remaining 88 bins.

Figure 3: Colors in Oil Paintings



Note: The panels display mosaic samples of paintings from the Web Gallery of Art (WGA) collection. For each hue range in the HSV (hue, saturation, value) color space, we show the 40 paintings with the highest share of pixels in the corresponding bin.

shifts in demand and taste, or broader economic and social transformations. To capture such dynamics, we construct color cycles, which measure how the prevalence of each color evolves from one generation of painters to the next.

For each country, we start with the color histograms described in the previous subsection. For painting i completed in year t, let $p_{i,c,t}$ denote the share of pixels in HSV bin c. We obtain yearly color series by averaging these painting-level shares across all paintings produced in year t: for each bin c, $x_{c,t}$ is the simple mean of $p_{i,c,t}$ over i. The sequence $\{x_{c,t}\}_t$ thus tracks, for each color bin, the evolution of the average pixel share over time. We winsorize each series at the 2nd and 98th percentiles and then apply a moving-average procedure,

$$\tilde{x}_{c,t} = \frac{1}{N_{c,t}} \sum_{j=0}^{S-1} x_{c,t-j},$$

where S denotes the averaging span and $N_{c,t} \leq S$ the number of available observations within the window. The change in prevalence of each color from one generation to the next is then given by

$$\Delta x_{c,t} = \tilde{x}_{c,t} - \tilde{x}_{c,t-S}, \tag{1}$$

where $\tilde{x}_{c,t}$ averages a color's share over the current block of S years, i.e. the interval $[t - S + 1, \ldots, t]$, and $\tilde{x}_{c,t-S}$ averages the immediately preceding, non-

overlapping block of the same length, i.e. the interval $[t-2S+1, \ldots, t-S]$. Their difference, $\Delta x_{c,t}$, therefore captures the change in prevalence of color c from one generation to the next: a positive value indicates that a given color has gained ground, while a negative value signals decline. This estimator is robust to missing years. We use $S = 20$ throughout as our benchmark.

These color-cycle series form the building blocks for our subsequent analysis: in the next step, we apply the robust PCA to condense the high-dimensional set of color dynamics into a few indices that can be systematically compared with economic activity.

3.4 Building the Color-Based Economic Index

To transform the 108-dimensional color-cycle panel into a single index, we apply robust PCA (Hubert, Rousseeuw and Vanden Branden, 2005).[5] This method extracts the dominant common factor s summarizing color changes, which we interpret as the latent economic signal embedded in paintings in the following way. Let

$$\mathbf{z}_t = \left(\Delta x_{1,t},\, \Delta x_{2,t},\, \ldots,\, \Delta x_{108,t}\right)'$$

denote the vector of color-cycle changes in year t.[6] Painting data can contain influential observations (*e.g.*, unusually large canvases, atypical palettes, or dating errors). Robust PCA downweights such outliers when estimating the covariance structure, yielding a first component that is stable to contamination yet asymptotically equivalent to classical PCA under Gaussian noise (Hubert, Rousseeuw and Vanden Branden, 2005).

We retain the first principal component only:

$$\hat{s}_t \;=\; \hat{\mathbf{w}}_1' \, \mathbf{z}_t,$$

[5] Robust PCA rather than classical PCA is important because a few years with atypical joint color compositions, for instance due to small numbers of surviving paintings or shifts in subject mix—can act as multivariate outliers even after univariate winsorization. Robust PCA downweights such year-level outliers so that the first component is driven by systematic co-movement in colors over time rather than by a handful of anomalous years.

[6] All features are standardized prior to PCA so that bins with different unconditional variances do not mechanically dominate the solution.

where $\hat{\mathbf{w}}_1$ is the loading vector associated with the largest robust eigenvalue. We normalize $\hat{s}_t$ to mean zero and unit variance within sample. The resulting score $\hat{s}_t$ is our color-based economic index. We compute it separately by country.

We depart from the benchmark specification in two cases. For France, we allow for a mid-seventeenth-century structural break in the color-generating process and estimate the PCA separately on the pre- and post-break samples before splicing the resulting series. This adjustment reflects a marked shift in French artistic production around the institutional reorganization associated with the Académie royale and the early Salon system in 1648. For Germany, where the annual sample is thinner, we set $S = 30$ rather than $S = 20$ in order to obtain a more stable benchmark series.

Section 5 summarizes a range of validation and robustness exercises showing that the resulting indices are not sensitive to the use of classical rather than robust PCA, to restrictions to indoor paintings, or to a narrower sample defined by a stable subject category, namely female portraits. The corresponding results are reported in detail in Appendixes B1 and B2.

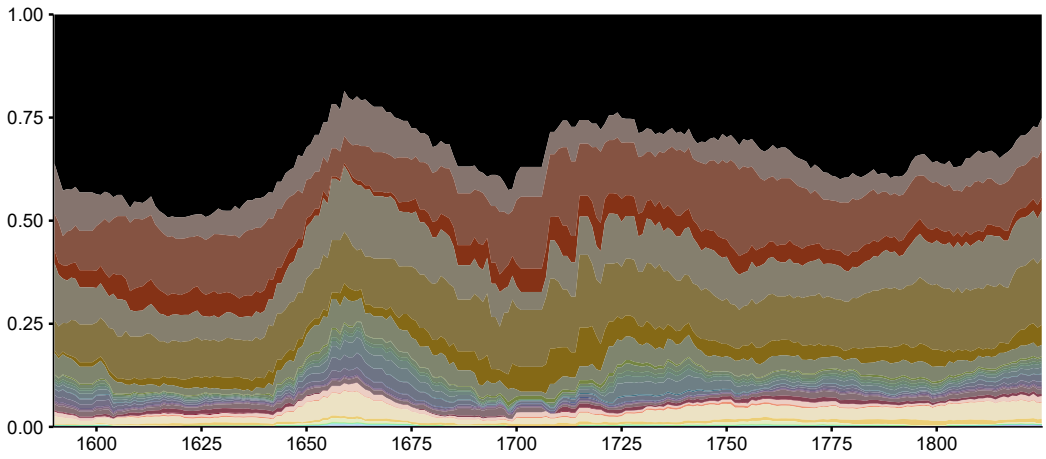
4 Chromatic Dynamics and Economic Fluctuations

This section examines how color use in European paintings evolved over time and how these chromatic changes relate to economic conditions. We begin with a detailed case study of Great Britain, where we document long-run patterns in color composition and interpret them against major historical and economic developments. We then analyze the color-based economic index, compare its dynamics with historical productivity reconstructions, and interpret the factor loadings in light of evidence from color historians. Finally, we extend the analysis to other countries—France, Holland, Italy, and Germany—to assess the cross-country consistency of the relationship between chromatic dynamics and economic fluctuations.

4.1 Chromatic Evolution and Economic Context in Great Britain

The relationship between different combinations of colors and the level of economic activity can be illustrated using two figures. Figure 4 shows the development of color combinations based on the 108 HSV color bins over the period from 1600 to 1820 measured in decades. It depicts the rolling mean per decade. The illustration clearly shows how the proportions of individual colors change over time. The proportion of dark colors fluctuates but decreases continuously. The black bin representing the darkest colors becomes less prevalent, brown and red tones also decline. At the same time, counter-cyclically to the dark tones, the number of light pastel tones becomes more pronounced.

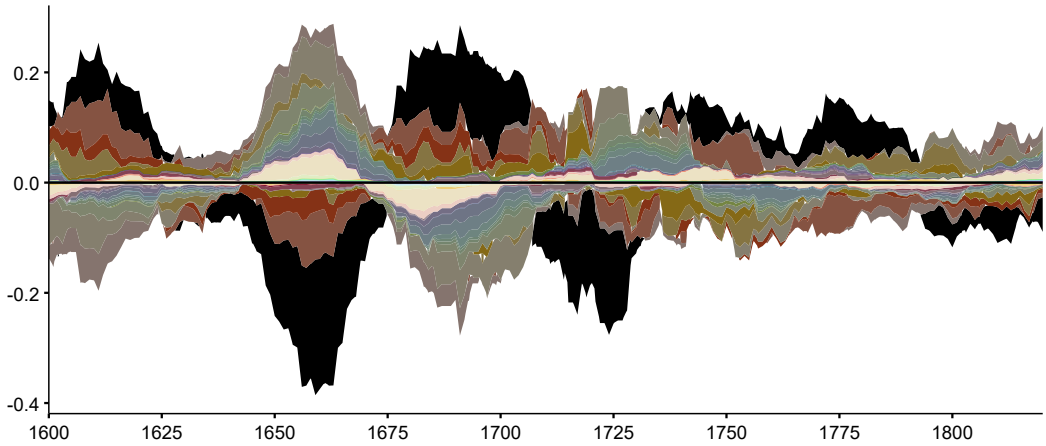
Figure 4: Color Shares Over Time in Great Britain



Note: The figure displays the 20-year moving-average share of each of the 108 HSV color bins in British oil paintings. The "black" bin is constructed by summing all pixels that fall into the darkest value category across all hue and saturation combinations.

Figure 5 then traces the decade-to-decade change in these color shares. The data indicate clear cyclical movements between darker and lighter palettes, reflecting alternating phases of contraction and expansion in material prosperity.

Figure 5: Change of Color Shares Over Time in Great Britain



Note: The figure displays 20-year changes in the shares of each of the 108 HSV color bins in English oil paintings. Each series reports the difference between two consecutive non-overlapping 20-year moving-average shares, as defined in Equation (1), so that positive (negative) values indicate an increase (decrease) in the prevalence of that color across painter cohorts. The "black" bin is constructed by summing all pixels that fall into the darkest value category across hue and saturation combinations.

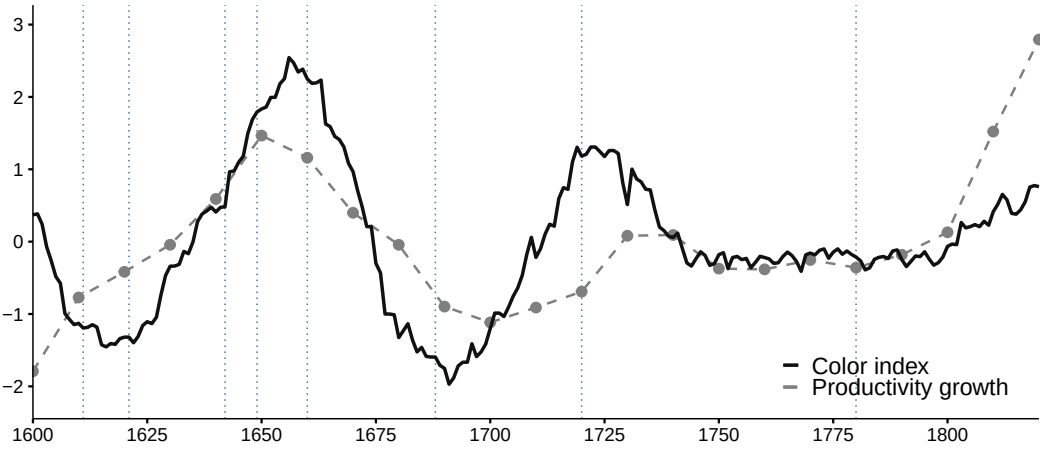
The early Stuart period (1604–1620s) is dominated by dark and muted tones, consistent with renewed fiscal pressures and rising tensions between crown and parliament.[7] From the 1620s onwards, brighter colors re-emerge and the bright color share increases until the 1660s. This period is characterized in the literature as a phase of economic transformation in agriculture and commerce reflecting the resurgence of overseas trade and colonial expansion. The English Civil War (1641–1652), which occurred precisely during this period, had no apparent influence on the shifts in color. This observation supports the thesis that the Civil War was embedded within a broader socio-economic transformation and that increased societal and political participation can be viewed as a positive aspect of this process (Yerby, 2019). This phase was then followed by a darker color phase with renewed instability in the 1680s: the Rye House Plot, Monmouth Rebellion, and Glorious Revolution. Historian John H. Plumb (1963) argued that rather than stabilizing Great Britain, the Revolution prolonged political unrest until 1715. The 18th century showed mixed signals—economic progress tempered by crises like the Seven Years' War, the 1772–73 credit crunch, the loss of the American colonies, and the onset of the Napoleonic Wars in 1793.

[7]For the major economic and political developments of the 17th century see Coward, 2003.

The 19th century brought a steady brightening, reflecting the Industrial and infrastructure revolutions, *Pax Britannica*, and London's rise as a financial hub.

Figure 6 compares the color-based index with the productivity index for Great Britain. The two indices move in parallel cycles. Three distinct growth phases emerge. The first extends from the early 17th century to the early 1660s; the second begins after the Glorious Revolution at the end of the century and continues into the 18th century; and the third starts at the end of the 18th century. These findings are consistent with recent economic and economic historical research that identified an increase in productivity beginning during the early 17th century related to higher agricultural productivity and trade and colonial expansion, a second much more modest growth period following the Glorious Revolution, and the onset of the Industrial Revolution at the end of the 18th century (Bouscasse, Nakamura and Steinsson, 2024).

Figure 6: Color Index for Great Britain



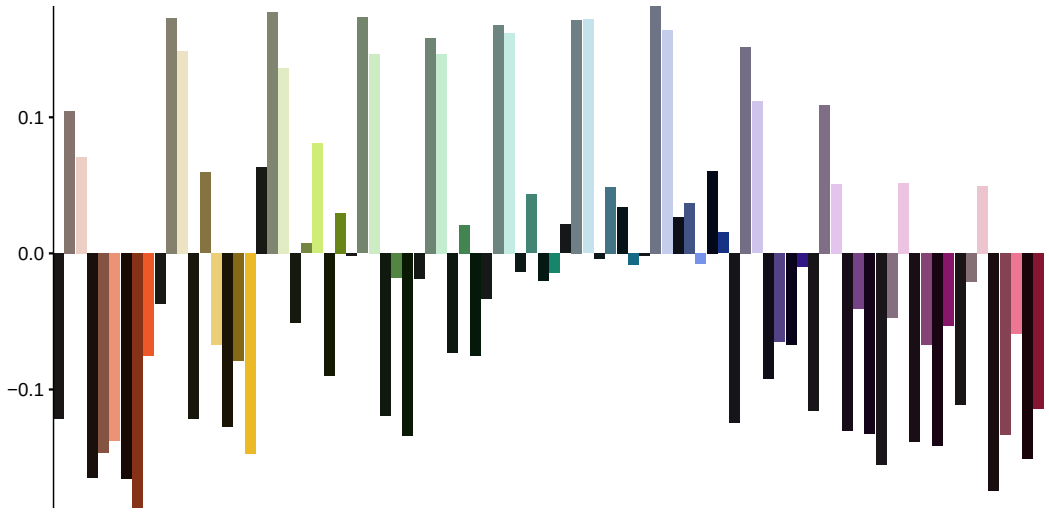
Note: The figure compares the color-based index and the historical productivity growth measure for Great Britain, 1600–1820. Both series are standardized to zero mean and unit variance for comparability. The color index summarizes annual changes in painting brightness and chromatic composition derived from the WGA dataset, while productivity growth follows the decadal estimates of Bouscasse, Nakamura and Steinsson (2024). We compute productivity growth as the change between adjacent two-decade (20-year) windows, consistent with the rolling-differences approach in (1). Dotted vertical lines mark major political and economic events: 1611 (James I dissolves Parliament), 1621 (Parliament asserts free speech), 1642 (start of the Civil War), 1649–1660 (Interregnum), 1688 (Glorious Revolution), 1720 the stock market crash of the South Sea Bubble, and 1780 (traditional start of the Industrial Revolution, following Rostow, 1960).

The color index, however, provides finer temporal detail. While the general growth of the 17th century can be explained by increased agricultural produc-

tivity and the expansion of trade and colonisation, we see some interesting institutional nuances here. After a decline that began with the first conflicts with the king and parliament and ended with their dissolution around 1611, the turning point, which occurred in the early 1620s at the latest, coincided with the dissolved Parliament's rebellion for the right to freedom of expression in 1621. The conflicts that now arose between Parliament and the King generated some small fluctuations in the color index, but they had very little effect on the rise of the index, and even the actual outbreak of the Civil War in 1642 had little effect. The growth of the colour index peaked during the Interregnum period and the starting decline coincided with the beginning of the Restoration period. This implies that institutional change, which gave Parliament greater influence, was an important economic driving force, and that any reverse effect, such as that seen during the Restoration period, had a negative impact. This also supports scholars who argued that for instance London as an engine of English economic growth was resilient to civil war activities (Coates, 2017). Secondly, the color index reveals a clear turning point following the Glorious Revolution (1688-1689). This is consistent with the institutionalist approach (North and Weingast, 1989), which suggests that the revolution had a positive impact on economic change. Accordingly, we identify the Glorious Revolution as a second wave of growth initiated by institutional change. However, the effect takes place in the first decades after the revolution and does not directly lead to the Industrial Revolution. The color index clearly shows that this period of growth came to a halt around 1720–1725 following the collapse of the South Sea Bubble in 1720. Researchers argue that, in addition to the aftermath of the crash—which led to increased financial market regulation—agricultural productivity also stagnated, Institutional gains have been exhausted, and Malthusian factors continued to play a role in restricting economic growth (Crafts and Mills, 2009; Clark, 2001). Finally, the color index rises a third time right after 1780. This is consistent with Rostow (1960), who claimed that the Industrial Revolution began after major technological innovations and investments in the 1760s and 1770s. However, the color index reveals a turning point, but no dramatic increase supporting claims by Crafts (1977) that change in growth rates were smoother.

Figure 7 finally depicts the factor loadings for Great Britain.[8] In line with our findings, dark colors such as black, brown and red, are related to negative factor loadings. Blue, green and light pastel colors are related to positive factor loadings. Finally, compared with the general color patterns described at the beginning of this section, we can observe some differences in the negative factor loadings. More precisely, red and yellow exhibit distinct patterns, which are also supported by Pastoureau (2019 and 2023b). Starting from the 16th century, red was predominantly relegated to a color used for distinguishing military and monarchical symbols. Only very bright reds—such as those produced with cochineal—were used in the clothing of the wealthy and aristocracy, while darker tones—such as madder—were considered suitable for the lower classes. From a religious perspective, the Anglican Church maintained a neutral stance toward the color red, although it became generally associated with immorality during the Victorian era. On a similar note, yellow was associated with treason and falsehood.

Figure 7: Factor Loadings for Great Britain



Note: The figure reports the factor loadings from the first principal component of HSV color shares in oil paintings produced in Great Britain between 1600 and 1820. Each bar corresponds to one of the 108 HSV color bins and shows its contribution to the color-based economic index for Great Britain, as obtained from the Hubert-type robust PCA procedure described in Section 3.

[8]For a general discussion of the role of the different colours in the historical context see Appendix H.

4.2 Cross-Country Evidence

This subsection summarizes the dynamics of the color-based indices and compares them with GDP estimates for the other major European economies. In addition, the individual factor-loading for each country is depicted.

Holland. Figure 8a compares the Dutch color-based economic index with historical GDP growth estimates (see Van Zanden and van Leeuwen, 2011), showing strong parallel movements between the two series. One difference is the sharper decline in GDP around 1640, which starts at a higher level (due to strong growth in the Netherlands at the end of the 16th century) and then rises again to the level of the color index by 1670.[9] The color index fluctuates less strongly during the 17th century reflecting a rather stable and not explosive growth with a rise at the beginning of the century and falls slightly after 1640, then continues to decline together with the GDP estimator in the first half of the 18th century. This decline can be explained by economic contraction and a loss of geopolitical supremacy, which is then followed by a joint rise of both series in the middle of the following century, accompanied by economic adjustment and recovery(de Vries and van der Woude, 1997).[10] Finally, a decline manifested itself in the 1770s at the latest, marked by domestic political tensions, and then ended with Napoleon's invasion in a trend reversal in the 19th century, although this happened slightly earlier in the GDP estimator.

Examining the factor loadings for the Netherlands, we observe overall the expected darker and brighter colour shades. We observe divergent effects for yellow and orange which are in the Netherlands positively associated Pastoureau, and green is negatively associatedPastoureau. Furthermore, red tones have a positive effectPastoureau. Furthermore, reddish tones have a positive effect. Dark purple tones can also be embedded in this positive association.

France Figure 8b compares the French color-based economic index with historical GDP growth estimates (see Ridolfi and Nuvolari, 2021), displaying

[9]The authors argue that this sudden decline in GDP estimates in 1650 is due to a combination of external shocks, such as wars impacting trade and poor harvests, as well as the exhaustion of the innovation cycles of the early Golden Age Van Zanden and van Leeuwen (2011)

[10]The comparatively strong growth of the Color Index around 1750–60, relative to the GDP estimator, supports Riley (1980)'s argument that the Netherlands, driven by Amsterdam, experienced extraordinary growth during that period due to a strong expansion of the financial markets.

a fairly parallel cyclical development between the color index and estimated GDP growth. The development begins around 1600 in a phase of political and economic stability, which ends with the assassination of King Henry in 1610 and leads to a regency crisis. Similarly, the Huguenot uprisings led to religious and political instability. This was accompanied by economic problems caused by the costs of war, increased debt and taxes. There were also crop failures and stagnation in trade. It was not until the reign of Louis XIV in the mid-17th century that political stability and economic prosperity returned.[11] This is also clearly visible in both time series. However, the king's international wars in particular, such as the War of Devolution (1667–1668), Dutch War (1672–1678), and the War of the Palatinate Succession (1688–1697) in particular led to international isolation and economic crisis. Religious restrictions also led to the flight of the Huguenots and a loss of human capital. Growth did not return until the 18th century. Early industrial development Proto-industry with the first machines was already in place at that time. Trade also grew during the 18th century. This rather growth-friendly period, which was also characterized by strong population growth, was clouded on the one hand by the Seven Years' War (1756-1763), which caused political and economic damage, but also by ever-increasing tensions of inequality, which erupted at the end of the century in 1789 in the French Revolution. Political and economic stabilisation did not follow until the 1810s. While both series run analogously until around 1740 and clearly reflect economic and political events, the color index continues to show a rather positive trend throughout the 18th century, except for the Seven Years' War, and it was only the Revolution that led to an abrupt decline. The GDP estimator shows a slight decline from the 1730s onwards,[12] with growth exploding shortly after the Revolution. In the color index, this only occurs with a delay. These positive deviations of the Colour Index in the 18th century from GDP estimates support the thesis that France was not generally characterised by stagnation, but already enjoyed some productivity gains (Horn, 2015).

The factor loading for France largely corresponds to expectations for dark and light tones. However, some light green tones deviate from the general predictions and cannot be related to exceptions in the literature.

[11] For the major economic and political developments during the 17th century see Crouzet (1966).

[12] The authors of the GDP estimates explain this is based on Malthusian pressure, where population growth outpaced agricultural production Ridolfi and Nuvolari (2021).

Italy. Figure 8c compares the Italian color-based economic index with historical GDP growth estimates (see Federico et al., 2024). An economic decline can be documented from the 17th century onwards, which occurs cyclically, with the cyclical fluctuations being more pronounced in the color index. It was not until the beginning of the 19th century, with the onset of the Industrial Revolution, that a trend reversal set in. The synchronicity of both indices is essentially broken twice. Once after the onset of decline at the beginning of the 17th century, which was exacerbated by the plague of 1629-31 (Cipolla, 1976*b*). followed by a brief economic recovery in GDP estimates, which cannot be found in the color index. This continues to point downward. In the second half of the 18th century, the color index indicates a recovery, which can potentially be explained by regional early industrial developments and the emergence of several political reform movements, as suggested by Cipolla, 1976*a*. However, this phase of upswing came to an end with the emergence of political tensions and ultimately the French Revolution. This 18th century upswing cannot be found in GDP estimates. [13]

The factor loading for Italy corresponds to the expected color combinations. We find dark tones negatively loaded and light tones positively loaded. We expect blue and green tones to be clearly positive, and brown and reddish tones to be negative. Yellow is positively associated in Italy Pastoureau.

Germany. Figure 8d compares the German color-based economic index with historical GDP growth estimates (see Pfister, 2022), showing that both series move together at the beginning of the 17th century, with the color index starting at a higher level. The decline in the early 17th century, even before the outbreak of the Thirty Years' War, is documented due to the economic losses suffered by southern Germany as a result of the emerging transatlantic trade. Following the Peace of Westphalia in 1648, both indicators recover slightly, signaling partial stabilization in a still fragmented empire. From the early to mid-18th century, the series diverged: GDP remains broadly stable, whereas the color index declines sharply, coinciding with the War of the Spanish Succession, the constitutional crisis of 1720, and the War of the Austrian Succession in the 1740s (Kleinehagenbrock, 2009). The renewed rise of the color index corresponds to Prussia's ascent to become a powerful territorial

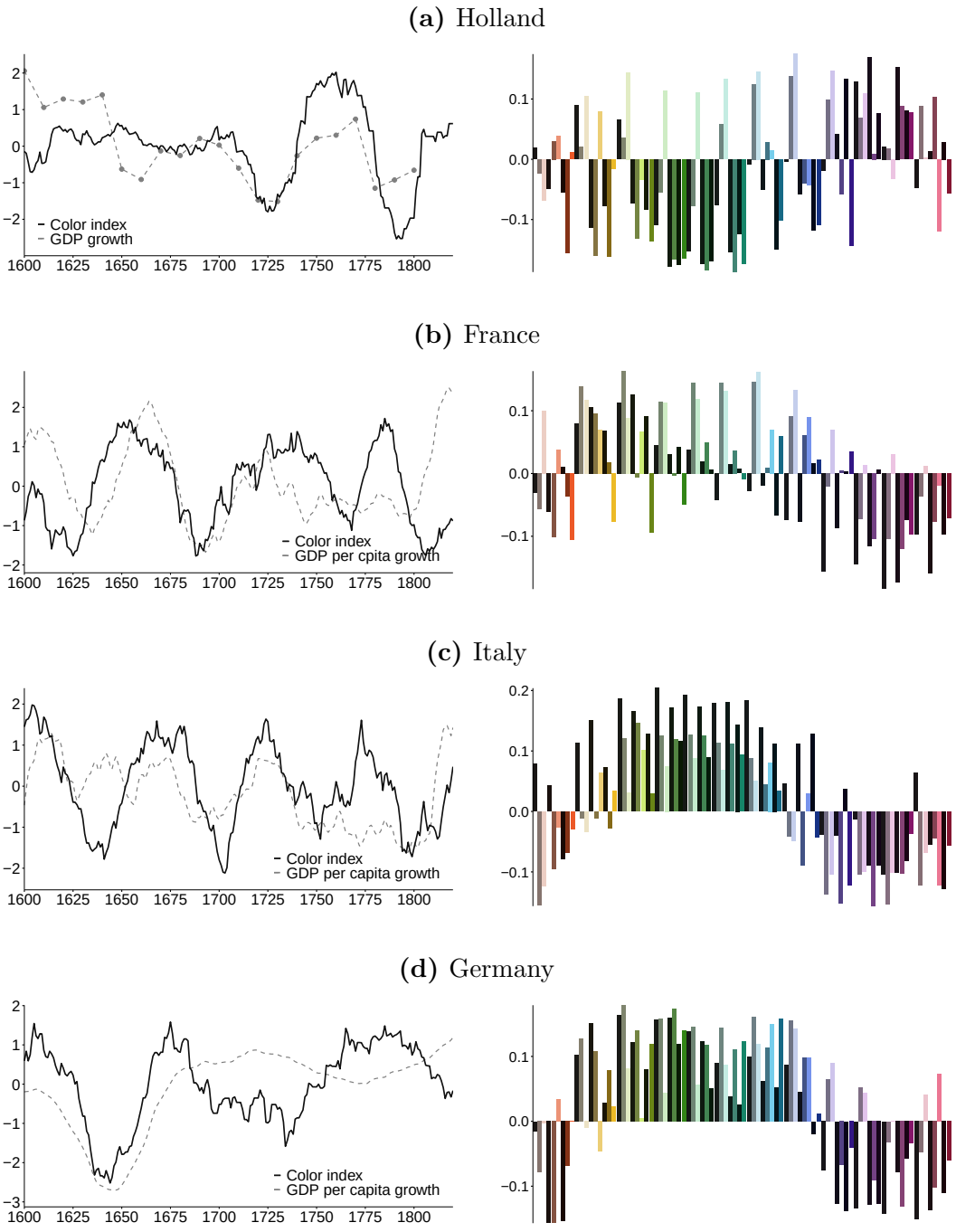
[13] Federico et al., 2024 attribute Italy's 18th-century economic decline to a combination of intense Malthusian pressures and rigid institutional structures that failed to adapt to shifting global trade routes. They do not comment on the plague of 1629-31.

state in a still fragmented Holy Roman Empire (Clark, 2006). The color index then collapses almost exactly with the outbreak of the Napoleonic Wars in 1792. Interestingly, such dynamics are missing in GDP estimates.[14]

The factor loading for Germany is very similar to that for Italy and corresponds to the expected dark and light shades. Here, yellow is negatively loaded, as is generally found Pastoureau.

[14]Pfister argues that, following the post-war recovery, Germany settled into a Malthusian plateau because, although many regions were in decline, some—such as Atlantic trading cities—experienced positive growth, which mitigated the overall decline. He also identifies a structural change around 1730 (as in the Color Index), but argues that the effects did not begin to yield positive growth until the 1750s. He also assigns less aggregate economic weight to the Napoleonic Wars.

Figure 8: Color Indices and Factor Loadings for European Countries



Note: The figure shows the color-based economic indices (left column) and their associated factor loadings (right column) for Holland, France, Italy, and Germany. The color indices and GDP growth series are standardized to zero mean and unit variance for comparability. Benchmark GDP data follow Van Zanden and van Leeuwen (2011) for Holland, Ridolfi and Nuvolari (2021) for France, Federico et al. (2024) for Italy, and Pfister (2022) for Germany (see Appendix A for a more detailed discussion). The PCA for France is split before and after 1648. The respective factor loadings for France represent the 1648–1820 subsample.

5 Robustness Checks and Validation Exercises

This section summarizes a set of complementary exercises designed to assess the robustness of the results of our color-based indices presented in Section 4. We address three questions. First, do the HSV measures extracted from paintings reflect observable conditions rather than purely artistic conventions? Second, are the indices robust to alternative samples and alternative ways of summarizing color information? Third, do the resulting series align with independent proxies for economic development? Detailed results are reported in Appendixes B1-B3.

5.1 Measurement Validity

Our interpretation of the color-based indices require that the colors and brightness depicted in paintings provide a faithful representation of past observable realities. A natural concern is therefore that the extracted HSV measures may reflect artistic conventions rather than actual historical conditions.

This concern is closely related to a long-standing debate on whether paintings reflect observed reality or are primarily shaped by artistic convention (see, *e.g.*, Goethe, 1810; Schopenhauer, 1816; Gombrich, 1960). We contribute to this debate by examining whether HSV measures—particularly brightness—comove with independent indicators of environmental and atmospheric conditions. Since direct visual recordings such as color photography are unavailable for the period under study, we rely on physical and phenological proxies for historical light conditions. Full results are reported in Appendix C3.

First, focusing on outdoor paintings, we test whether measured brightness is related to albedo, *i.e.*, the share of solar radiation reflected by the Earth's surface, and historical precipitation data from Pauling et al. (2006). If painters captured real lighting conditions with some regularity, variation in reflected light and weather should be visible in the value component of the image. Using a flexible regression framework with a rich set of controls, we find that both albedo and precipitation are selected as significant predictors of brightness. This suggests that paintings capture meaningful variation in environmental lighting conditions.

Second, we exploit annual data on grape must sugar content in Southern Germany (Pfister et al., 2024), a well-established proxy for solar radiation and favorable growing conditions. Estimating regressions with city fixed effects and time trends, we find that brighter paintings are positively and significantly associated with higher sugar content. This relationship does not appear in other European regions, reinforcing the interpretation that the value component reflects local environmental conditions rather than generalized stylistic trends.

Third, we examine the impact of the 1783 eruption of the Icelandic volcano Laki, which generated a major atmospheric shock across Europe by releasing sulfur dioxide in quantities estimated to be several times modern annual industrial emissions (Thordarson and Self, 2003). In a narrow event window around the eruption, paintings become systematically darker. This result provides particularly transparent evidence that the visual properties we measure respond to exogenous changes in atmospheric conditions, consistent with physical accounts of the event (Zerefos et al., 2007).

Taken together, these exercises support the interpretation that HSV measures capture meaningful features of the observed environment, rather than merely reflecting the internal conventions of artistic production.

5.2 Robustness of Index Construction

We next assess whether our results depend on specific modeling choices or on the composition of the painting sample. The corresponding exercises are reported in Appendixes B1, B2, and B3.

A first concern is sensitivity to the statistical method used to summarize the high-dimensional color information. In the baseline analysis, we use robust principal component analysis in order to reduce the influence of outliers. Reassuringly, the resulting indices are very similar when we instead use standard PCA, indicating that the main patterns are not driven by a small number of atypical observations (Appendix B2).

A second concern is that some genres may mechanically affect measured brightness or color composition. Outdoor scenes, for example, may contain more sky and therefore more light pixels, while changes in genre composition over time

could alter the aggregate palette independently of economic conditions. To address this issue, we recompute the indices on increasingly restrictive subsamples. We first restrict attention to indoor paintings, where artificial illumination and interior material conditions are likely to be most relevant. We then consider a narrower subset of female portraits, which provides a comparatively stable subject category over time. In both cases, the resulting indices remain close to the baseline series (Appendix B1).

A third concern is that the long-run evolution of color may be affected by ageing, varnish yellowing, or pigment fading. To address this possibility, we re-estimate the indices using coarser color groupings that are deliberately less sensitive to fine distinctions in hue. Specifically, we collapse the original 108 HSV bins into broad color families and show that the main turning points and cross-country patterns remain intact. The stability of the results under these increasingly coarse recodings suggests that our findings are not driven by conservation-related drift or by small movements across narrowly defined hue categories (Appendix B3). Finally, as additional robustness checks, we draw on information from various editions of *Analysis of Paint Media*, primarily authored by the conservation scientists John S. Mills and Raymond White and published in the National Gallery of London *Technical Bulletin* from 1977 to 1996.[15] In this bulletins, the authors extract samples from paintings and compile detailed, among other information, analytical records for each artwork, documenting the artist, painting, date, sample location, and oil type to characterize historical paint media practices. The dataset includes 263 oil paintings by 181 artists, comprising 728 samples that employ three oil types (*i.e.*, linseed, walnut, and poppy). This analysis reveals two principal stylized facts. First, depending on time and space, artists tend to maintain for the same colors for the same materials. Second, oil type appears to be closely associated with the painter's geographic location. In light of these stable relationships over time, any differences emerging from the PCA should control for the potential ageing and deterioration of pigments.

Overall, the color-based indices are robust to alternative estimators, alternative samples, and alternative aggregations of the underlying HSV information.

[15]The bulletins can be downloaded at the following link `https://www.nationalgallery.org.uk/research/research-resources/technical-bulletin`

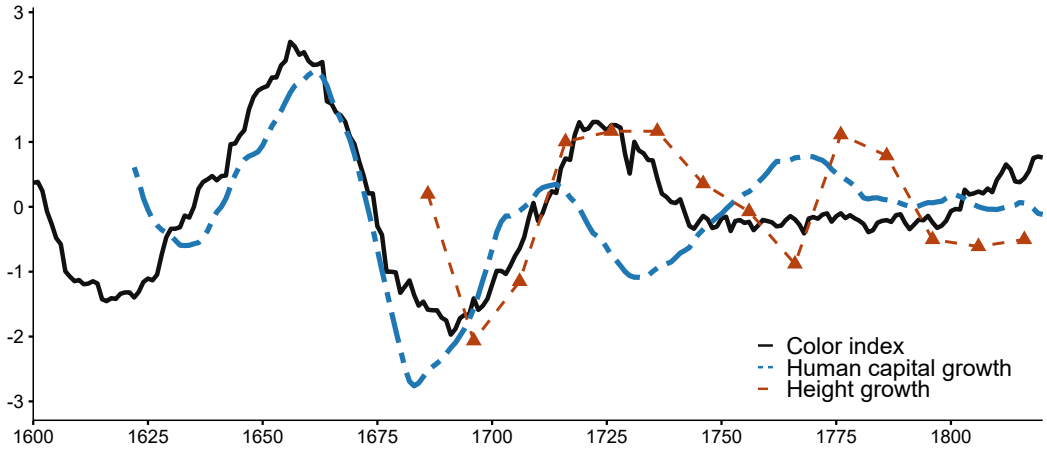
5.3 Validating Color as a Historical Measure

In this subsection, we compare the color-based indices with independent proxies for economic development. At the macro level, Section 4 already compares the country-specific color indices with existing reconstructions of GDP or productivity. Beyond these benchmarks, the only two cliometric time series that, to the best of our knowledge, are available for our period that allow comparison across the five countries considered are height, drawn from Koch, Stojkoski and Hidalgo (2024)), and the recently constructed measure of academic human capital by Curtis et al. (2026).[16] Height is available at five-year intervals, whereas the human-capital series provides annual observations. At the city level, Appendix C1 shows that painting-based color measures are systematically related to urban population; in particular, colors in the blue range are positively associated with larger cities in the city-period specification, although the individual color coefficients are naturally noisier across specifications.

Figure 9 compares the color index for Great Britain with the height and human capital index for universities. Figure C1 in Appendix C1 provides the corresponding comparisons for all the countries in the sample. Overall, our color indeces co-move closely with the established cliometric proxies for economic development supporting the validity of our measures.

[16]The main goal of the article of Koch, Stojkoski and Hidalgo (2024) is to propose a new indicator of GDP per capita at the regional level, constructed using an elastic net regression, a machine learning technique. However, we cannot use this indicator because the countries included in our analysis are part of the training dataset.

Figure 9: External validation for Color Index for Great Britain



Note: The figure compares the growth rate of the color-based index, the human capital index for universities, and height for Great Britain over the period 1600–1820. For comparability, and given its exponential trend, we use the detrended logarithm of each variable. All series are standardized to zero mean and unit variance for comparability. For the detrended logarithm of the human capital index we compute the change between adjacent two-decade (20-year) windows, consistent with the rolling-differences approach in (1).

6 Conclusion

This paper has proposed and implemented a novel approach to measuring long-run economic activity by quantifying the color composition and brightness of historical artworks. Our starting hypothesis is that, since artificial light in modern times is a reliable indicator of human activity and a robust proxy for GDP, information on the color composition of light can be used to infer patterns of economic growth in the past. Drawing on more than 12,000 digitized European oil paintings from 1600 to 1820, we have shown that the chromatic properties of visual art—when treated as quantitative data—encode systematic information about material and technological conditions. By decomposing paintings into HSV components and summarizing their temporal dynamics through principal component analysis, we have constructed color-based indices that closely track known patterns of economic expansion and contraction across European regions.

Our findings highlight three main results. First, the long-run evolution of brightness and color in paintings corresponds closely to established narratives of economic growth. In Great Britain, for example, the color-based index

identifies three major cycles that align with key historical turning points: the early seventeenth-century rise in agricultural productivity and trade, the institutional transformation following the Glorious Revolution, and the acceleration associated with the Industrial Revolution. Second, the color indices capture cross-country variation in economic trajectories. While the Dutch index mirrors the rise and decline of the Golden Age, the French series reflects the cycles of instability and recovery surrounding the Revolution, and the German and Italian series trace the uneven transition from regional fragmentation toward industrialization. Third, factor loadings reveal consistent economic symbolism: darker and muted tones such as black, brown, and red correlate negatively with activity, whereas blue, green, and light tones are associated with expansion. These patterns echo both material constraints—such as pigment availability—and enduring cultural associations identified by color historians.

Beyond its historical application, the paper makes a methodological contribution. It demonstrates how cultural artifacts can be transformed into measurable data for economic analysis, providing a bridge between qualitative evidence and quantitative inference. The approach extends the logic of luminosity-based proxies, such as satellite night lights, to periods long preceding modern data collection. The HSV framework and robust PCA methodology offer transparent and replicable tools for extracting economic signals from high-dimensional visual information.

More broadly, the results show that art, often viewed as a mirror of society, also serves as a measurable record of its material underpinnings. Turning images into data allows us to recover aspects of economic life that conventional statistics cannot capture, particularly in periods where monetary or output data are sparse or unreliable. Future research could extend this framework to other forms of cultural production—architecture, photography, or design—and combine visual features with textual or network-based information to study the diffusion of ideas, technologies, and tastes.

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Colors of Growth

Online Appendix

by Lars Boerner, Tim Reinicke, Samad Sarferaz, and Battista Severgnini

A Data and Preprocessing

This section outlines the steps undertaken to translate the images of the paintings into data, focusing in particular on the quantification of colors and the geolocation of the artworks.

A1 Color Data

Treating outliers. We begin by scanning all pixels in the image and counting the frequency of each distinct HSV color. If one color is substantially more common than any other (specifically, at least 15 times more frequent than the second most common color), we interpret this as indicating a flat background or border. All pixels matching this dominant color are then removed. From the remaining pixels, we retain enough to form a square array and reshape them into a smaller, cleaned image.[17]

A2 Location of Data

Regarding geocoding, we matched the painting catalogue to contemporary city datasets and standardized the reported locations of artists. The catalogue was merged with the WorldCities and GeoNames databases, restricted to European cities.[18]. Entries from both sources were linked by geographic proximity (latitude–longitude) and relative population to build a multilingual dictionary of city names and aliases, each associated with coordinates and administrative codes. The dictionary was then cleaned by removing very short or noisy

[17] We exclude the cycle of paintings by Eustache Le Sueur (1617–1655) depicting scenes from the life of St Bruno and related episodes (including the death of Raymond Diocrès), all oil on canvas, Musée du Louvre, Paris (Web Gallery of Art), as the depicted objects and image types could bias the color analysis.

[18] The databases are available at `https://www.geonames.org/` and at `https://www.worldcitydb.com/`

aliases, standardizing name formats, and expanding the data to one row per city–alias pair. Aliases were ranked by their position in the string and by city population so that common variants of large cities took precedence.

Free-text birth and death place strings in the catalogue were normalized through text cleaning to extract location tokens. Using rule-based matching, we assigned up to three candidate cities—interpreted as birth place, death place, and an additional location—to each artist, and merged the corresponding identifiers, coordinates, and country codes back into the painting-level dataset.

A particular adjustment was required for the boundaries of Holland, which changed markedly over the early modern period. In line with the GDP data of Van Zanden and van Leeuwen (2011), we restrict the Dutch sample to the historical province of Holland. The retained set of cities therefore includes Alkmaar, Amsterdam, Bodegraven, Delft, Dordrecht, Enkhuizen, Gorinchem, Gouda, Haarlem, Heemstede, Heusden, Hoorn, Leiden, Middelharnis, Naaldwijk, Oud-Beijerland, Rijswijk, Rotterdam, Scheveningen, Schiedam, The Hague, Uithoorn, Weesp, Woerden, Zaandam, and Zoeterwoude.

A3 GDP Data

England, decadal productivity. For England, we rely on the productivity series compiled by Bouscasse, Nakamura and Steinsson (2024), who estimate total factor productivity (TFP) from 1250 to 1870 using a Malthusian model with land and labor. Their decadal averages of real wages and population imply TFP growth rates of approximately zero before 1600, around 2 per cent per decade between 1600 and 1800, and about 5 per cent per decade after 1810. We use the *mlq mean* series from their replication files as a proxy for England's economic performance, interpreting it as an indicator of growth rather than of levels.

France, annual GDP per capita. We employ the demand-side GDP-per-capita reconstruction of Ridolfi and Nuvolari (2021), which provides annual estimates for France between 1280 and 1850. Agricultural output is inferred from food demand (based on wages and price indices), while non-agricultural output is derived from urbanisation rates and relative productivity. The estimates are expressed in 1990 international dollars. For the nineteenth century, we splice this series to the Maddison Project's real GDP-per-capita data

for France (constant 2011 international dollars), which incorporate multiple purchasing-power-parity benchmarks.

Holland , decadal GDP. Our benchmark series for the Holland is the GDP reconstruction for this Dutch province by Van Zanden and van Leeuwen (2011). The authors compile national accounts estimates for 1347–1807, calculating value added in agriculture, industry, and services at both current and constant prices. After deflating current-price output using contemporaneous price indices (expressed in guilders of 1800), the published data report GDP and population at a decadal frequency. We use their constant-price GDP series (not per capita) and aggregate observations for cities historically located in Holland to construct a provincial measure.

Italy, annual GDP per capita. For Italy, we draw on the demand-side GDP-per-capita estimates of Federico et al. (2024). The authors compile nearly 95,000 wage and price observations from 169 locations and estimate agricultural output per capita from a demand function using real wages and price indices. Non-agricultural output is inferred from urbanization rates and relative productivity, and the resulting GDP-per-capita index is expressed in 1990 Geary–Khamis dollars via a purchasing-power-parity exchange rate. The series cover both the Centre–North and the South and are available at annual frequency; we downloaded the data on 28 April 2025. As the study is a CEPR Discussion Paper, the series may be subject to revision upon publication.

Germany, annual real GDP-per-capita index. Pfister (2022) constructs a real GDP series for Germany covering 1500–1850 using an indirect output estimation approach. The method combines data on wages, prices, and sectoral employment to derive a Fisher quantity index, chained across adjacent years and normalised to 1851 = 1. As the index represents real GDP per capita, we subsequently convert it into growth rates to ensure cross-country comparability.

To place the heterogeneous series on a common footing, we compute and standardise log growth rates. Specifically, we calculate the log growth of GDP (or GDP per capita) over two-decade windows for the Holland, Italy, France, and England, and over three-decade windows for Germany. Smoothing over 20 years (30 years for Germany) reduces short-term volatility. Each resulting

growth series is then standardised to have zero mean and unit variance before inclusion in the main analysis.

B Robustness Checks

B1 Object-Based Indices

To assess whether our color-based indices reflect underlying economic conditions rather than shifts in location or subject matter, we re-estimate the indices on two content-consistent subsets: indoor scenes and female portraits. Outdoor scenes can mechanically increase brightness due to skies and seascapes, while focusing on a subject represented throughout the entire period allows us to test whether our econometric strategy remains consistent when holding subject matter constant. Concentrating on motifs with comparable compositional structures across centuries and countries helps to mitigate this source of bias.

B1.1 OpenAI CLIP

We use a pre-trained vision–language model, Contrastive Language–Image Pre-training (CLIP) developed by Radford et al. (2021), to assign content labels to paintings in a consistent and replicable manner, and to construct robustness subsets. CLIP embeds images and short text prompts into a shared latent space and measures their cosine similarity, enabling zero-shot classification: without task-specific training, a painting can be scored against prompts such as "indoor" or "female portrait." This provides a uniform, metadata-independent filter applicable across countries and years.

We implement the classifier using the ViT-B/32 CLIP variant. For each image, we compute cosine similarities with a fixed set of prompts (listed below), normalize them, and interpret the resulting values as inclusion scores. Unless otherwise noted, paintings with a similarity score of at least 0.75 for the relevant label are retained. For female portraits, we further require that the Web Gallery of Art (`type`) field identifies a portrait to minimise false positives.

CLIP is used solely to define these subsets; the remainder of the analytical pipeline remains unchanged. Econometrically, this approach limits researcher degrees of freedom and introduces an out-of-sample, portable classification rule, since the model is pre-trained on generic image–text pairs rather than on our data. The robustness exercises then test whether the resulting indices remain stable when restricted to scenes dominated by indoor illumination (for "indoor") or by time-consistent depiction conventions (for "female portrait").

Figure B1: Illustration of CLIP-Based Content Classification



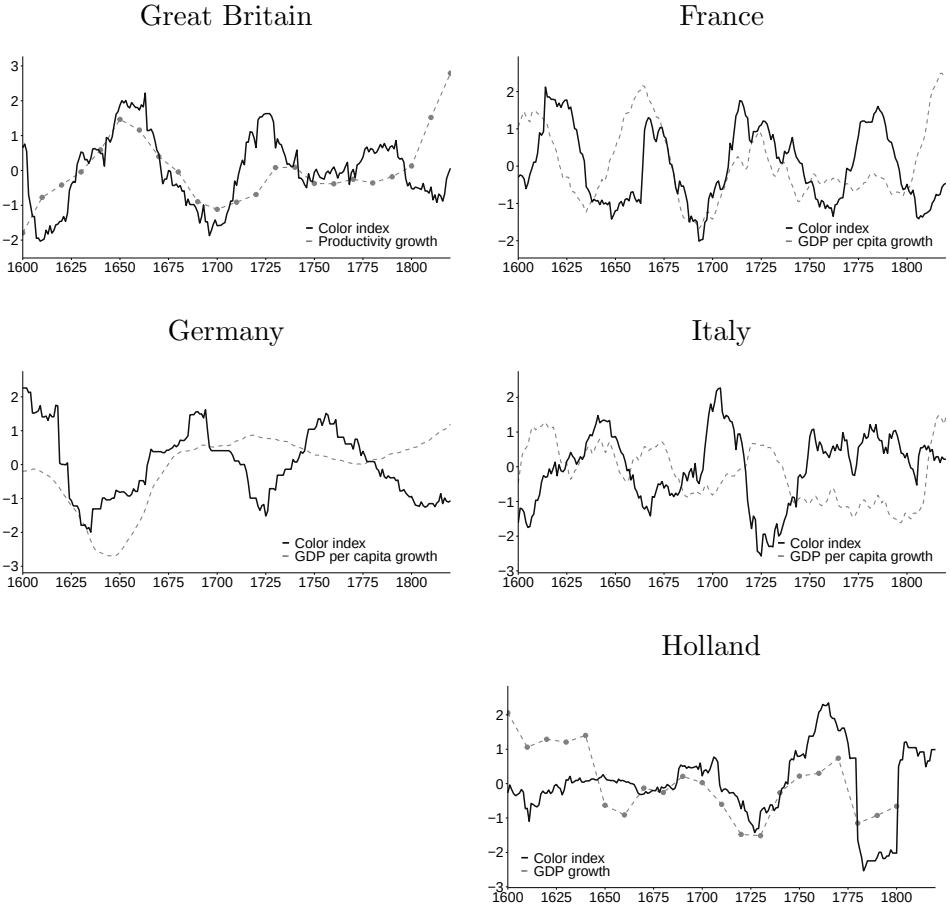
Note: Each panel displays an example painting from the WGA dataset together with the CLIP-based similarity score (reported as a probability) for a given text prompt (e.g., "female portrait", "positive emotion", "fire", "outdoor scene"). These scores are used to construct the content labels described in Section B1.1 and to define the robustness subsets (indoor scenes and female portraits) used in the main analysis. The CLIP model (Radford et al., 2021) is pre-trained on generic image–text pairs and is not fine-tuned on our data.

B1.2 Indoor and Outdoor Paintings

Outdoor composition may inflate measured brightness via sky exposure or changing landscape shares. By contrast, interior scenes concentrate on illumination that is plausibly tied to economic fundamentals such as artificial lighting, glazing, mirrors and interior reflectance. We therefore restrict the sample

to paintings classified as *indoor* by the classifier with a similarity score ≥ 0.75 and re-estimate the color-based index on this subset. Results are reported in Figure C1.

Figure B2: Color Indices from Indoor Motives



Note: The figure shows the color-based economic indices and their corresponding benchmark growth series for Great Britain, France, Germany, Italy, and Holland over the period 1600–1820. The indices are constructed from the same WGA sample as in the main text, but restricting to paintings classified as indoor scenes with a predicted indoor probability above 75%, based on the image classifier of Radford et al. (2021). The color indices summarize annual variation in painting brightness and chromatic composition. Benchmark GDP or productivity data follow Bouscasse, Nakamura and Steinsson (2024) for Great Britain, Van Zanden and van Leeuwen (2011) for Holland, Ridolfi and Nuvolari (2021) for France, Federico et al. (2024) for Italy, and Pfister (2022) for Germany (see Appendix A for a more detailed discussion). All series in each panel are standardized to zero mean and unit variance to facilitate comparability across countries.

B1.3 Female Portraits

Portraits occupy a central position in the history of Western art and has long been central to the articulation of individual identity.[19] They offer a relatively time-consistent subject: pose types and formats (bust, half-length, three-quarter, full-length) remain remarkably stable and serve enduring social functions such as identity, status, and commemoration. By contrast, still life and landscape genres exhibit pronounced fluctuations and shifting subgenre between 1600 and 1830, making them less comparable over time.

Female portraiture is particularly suitable for our purposes. It is typically set indoors and concentrates visual information on garments and skin tones, precisely where pigment availability, dye technology, and textile trade leave a material trace. While the share of female portraits is itself culturally and economically informative, here we use this subset primarily to test the robustness of our indices to content restrictions. Each painting is scored against a set of thematic prompts capturing subject matter and composition.[20]

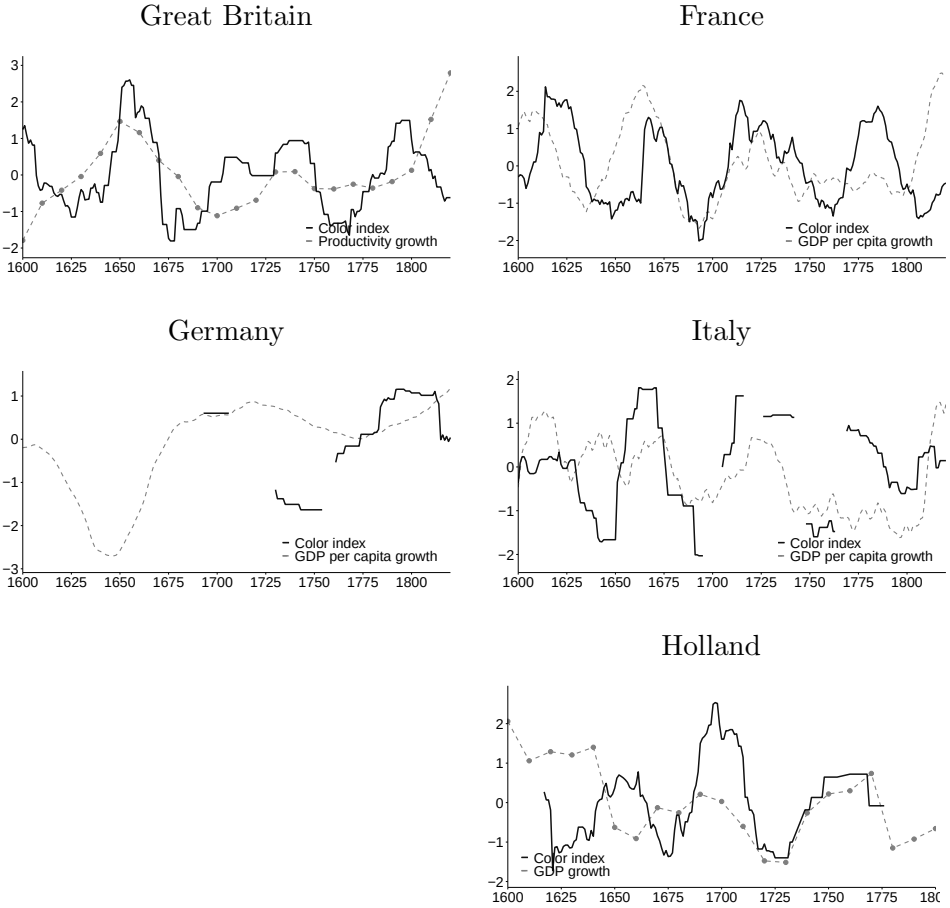
A painting enters the female-portrait subset if (i) its CLIP similarity score for the first (female) prompt is at least 0.75, and (ii) the WGA `type` field identifies it as a portrait (oil on canvas or panel, as in the baseline sample). The remaining prompts are used to normalize similarities across heterogeneous content types but do not directly determine inclusion.

We then rerun the analysis pipeline without modification on this restricted sample.

[19] Woodall (1997) discusses the role of portraits in the construction and representation of individualism.

[20] The prompts include: (i) a prominent female figure as the central subject; (ii) a prominent male figure as the central subject; (iii) a detailed still life or non-human focus; (iv) a crowded scene with many people (e.g., town, marketplace, battlefield); (v) a religious figure such as the Virgin Mary or a saint; (vi) a landscape without visible humans; (vii) a ship in water; and (viii) a townscape without visible humans, all within historical artworks.

Figure B3: Color Indices from Female Persons Indoors



Note: The figure shows the color-based economic indices and their corresponding benchmark growth series for Great Britain, France, Germany, Italy, and Holland over the period 1600–1820. The indices are constructed from the same WGA sample as in the main text, but restricting to paintings that depict a female figure: we use a CLIP-based classifier (Radford et al., 2021) to identify works with a predicted probability above 75% that a female person is present, and intersect this with the WGA type metadata that records portrait subjects. The color indices summarize annual variation in painting brightness and chromatic composition. Benchmark GDP or productivity data follow Bouscasse, Nakamura and Steinsson (2024) for Great Britain, Van Zanden and van Leeuwen (2011) for Holland, Ridolfi and Nuvolari (2021) for France, Federico et al. (2024) for Italy, and Pfister (2022) for Germany (see Appendix A for a more detailed discussion). All series in each panel are standardized to zero mean and unit variance to facilitate comparability across countries.

B2 Alternative Index Constructions

To examine whether the color-based economic indices are sensitive to alternative implementation choices. We focus on two margins: the dimensionality-reduction method used to extract the common factor and the averaging span S used to construct the color cycles. Across both exercises, the time path of the indices remains broadly stable.

B2.1 Standard PCA

As a first robustness check, we recompute the indices using standard principal component analysis (PCA) rather than the robust PCA estimator used in the main text.

B2.2 Different Averaging Spans

As a second robustness check, we vary the averaging span S used to construct color cycles from adjacent non-overlapping S-year blocks. This assesses whether the benchmark results are sensitive to the degree of temporal smoothing built into the index.

B3 Fading and Conservation of Colors

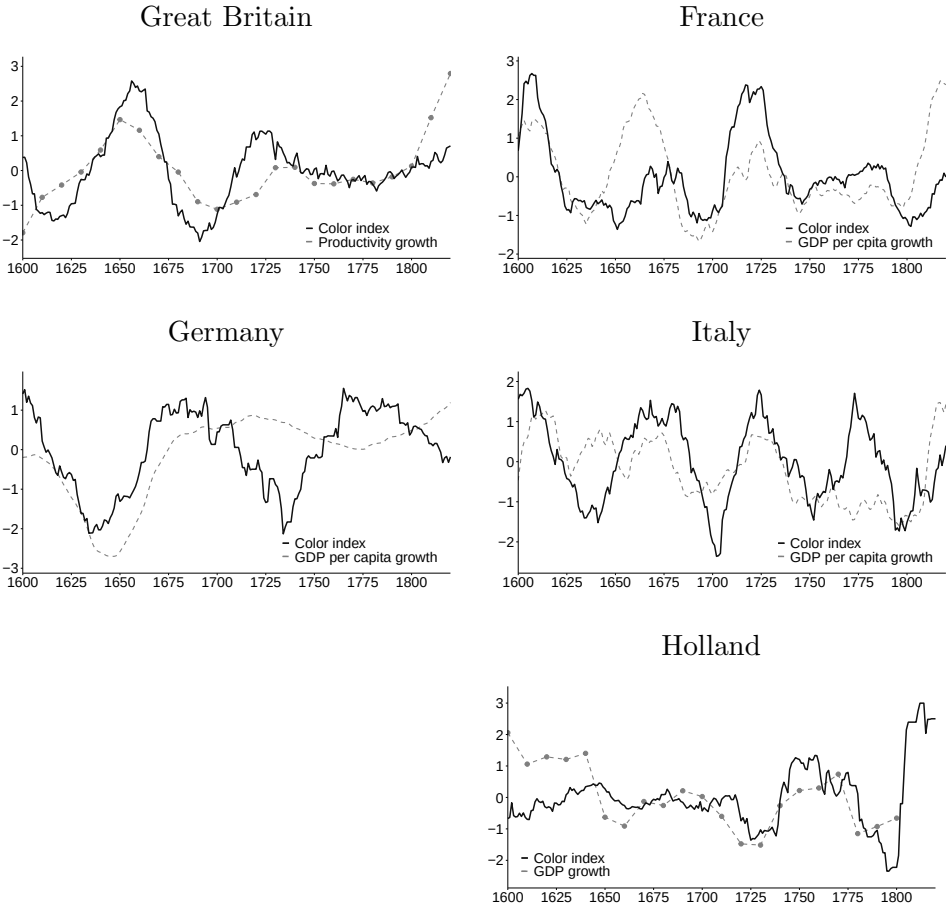
B3.1 Six color families

Threat addressed. Yellowing and desaturation can blur fine hue distinctions and push pixels toward the achromatic axis.

Recoding. We collapse the 108 HSV bins into six blocks: (i) black/dark ($v = 0$), (ii) neutral white/grey ($s = 0$, $v > 0$), (iii) warm hues (reds/oranges/ochres), (iv) green and yellow-green (including the yellow–amber boundary bins to reduce sensitivity to global yellowing), (v) cyan/blue, and (vi) purple/magenta.

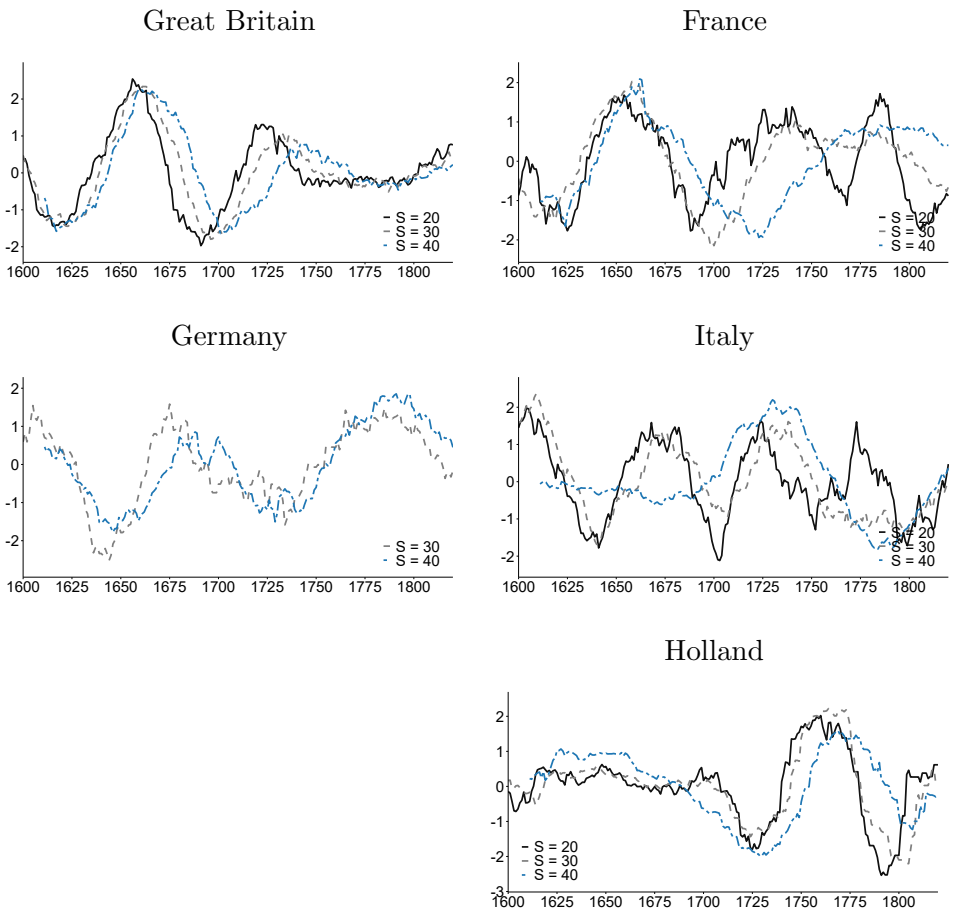
Interpretation. This specification preserves the main coarse contrasts (dark vs. light-neutral; warm vs. cool; green vs. non-green) while discarding within-family variation that is most fragile to fading. If results were driven by gradual conservation drift, one would expect the blocked index to change materially

Figure B4: Color Indices Based on Standard PCA



Note: The figure shows the color-based economic indices and their corresponding benchmark growth series for Great Britain, France, Germany, Italy, and Holland over the period 1600–1820. The color indices summarize annual variation in painting brightness and chromatic composition derived from the WGA dataset and are constructed using standard principal component analysis (PCA), rather than the robust PCA estimator used in the main text. Benchmark GDP or productivity data follow Bouscasse, Nakamura and Steinsson (2024) for Great Britain, Van Zanden and van Leeuwen (2011) for Holland, Ridolfi and Nuvolari (2021) for France, Federico et al. (2024) for Italy, and Pfister (2022) for Germany (see Appendix A for a more detailed discussion). All series in each panel are standardized to zero mean and unit variance to facilitate comparability across countries.

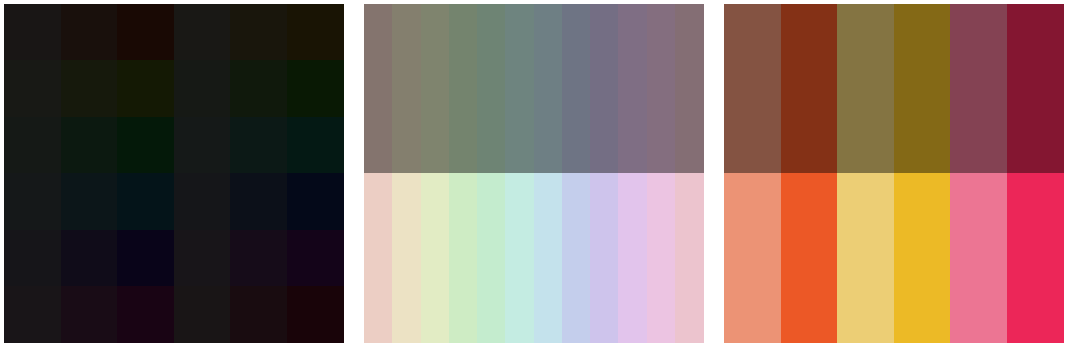
Figure B5: Color Indices under Alternative Averaging Spans



Note: The figure reports the color-based economic index under alternative averaging spans used to construct color cycles from adjacent non-overlapping S-year blocks. For Great Britain, France, Italy, and Holland, the index is shown for $S \in \{20, 30, 40\}$. For Germany, the panel reports $S \in \{30, 40\}$, reflecting the thinner annual sample. All series are standardized within country to zero mean and unit variance. The benchmark specification uses $S = 20$, except for Germany, where it uses $S = 30$.

once these distinctions are removed; if the signal reflects broader compositional and illumination changes, timing and turning points should remain similar.

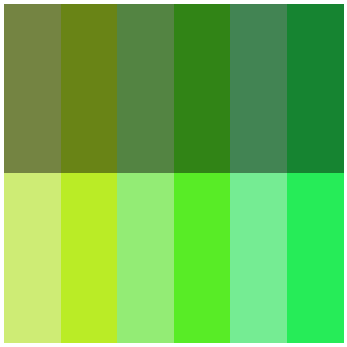
Figure B6: Six HSV color blocks used for fading robustness



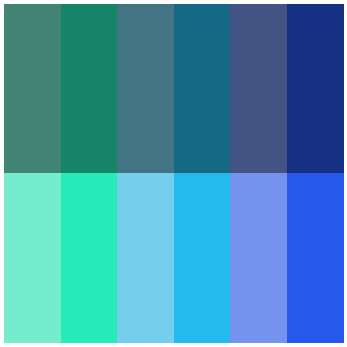
(a) Black / dark ($v = 0$)

(b) Neutral white/grey ($s = 0$, $v > 0$)

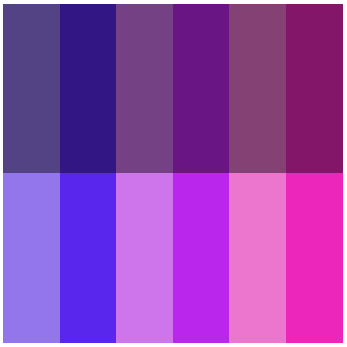
(c) Warm hues (red/orange/ochre)



(d) Green / yellow-green



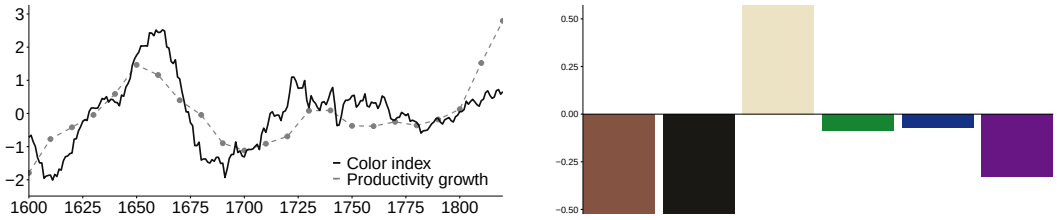
(e) Cyan / blue



(f) Purple / magenta

Note: Each panel shows one block formed by aggregating multiple bins from the 108-bin coarse HSV discretization (12 hue × 3 saturation × 3 value). The small tiles are the underlying HSV bins included in the block; tile colors follow the fixed HSV-to-HEX mapping used throughout the analysis.

Figure B7: Great Britain: blocked color index and loadings (six blocks)



(a) Blocked color index **(b)** PC1 loadings on blocks

Note: The index is re-estimated after replacing the 108 HSV-bin shares with the six block shares in Figure B6. The right panel reports the corresponding PC1 loadings on the six blocks.

B3.2 Four color families

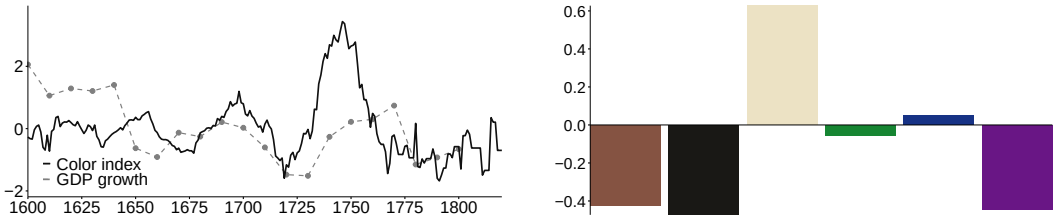
Threat addressed. Even with six families, ageing could still matter if varnish yellowing and chroma loss systematically move many pixels toward the achromatic axis, making the split between "dark" and "neutral" itself unstable over time.

Recoding. We therefore collapse all near-achromatic bins into a single *achromatic* block: this includes (i) all low-value bins ($v = 0$), where hue is effectively undefined, and (ii) all low-saturation bins ($s = 0$, $v > 0$), which correspond to greys/whites where small conservation shifts (yellowing or desaturation) would otherwise reclassify pixels between "neutral" and nearby chromatic families. The remaining chromatic bins are grouped into three coarse hue families: *warm* (red/orange/ochre, optionally including the yellow boundary), *green* (yellow-green/green), and *cool* (cyan/blue plus purple/magenta).

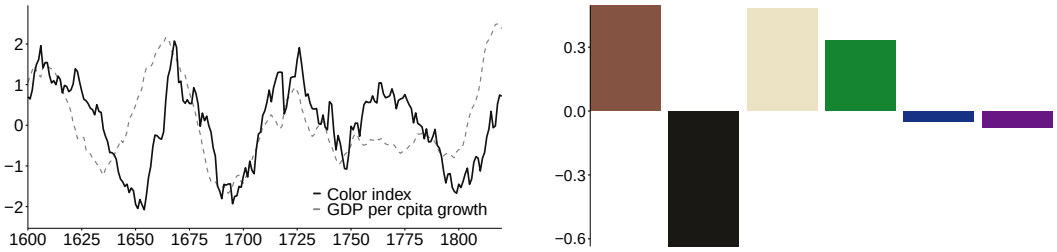
Interpretation. In the four-block recoding, PC1 loads strongly and positively on the achromatic block and negatively on warm tones in every country (France differs only up to the arbitrary sign of the PCA, which we orient for comparability). This pattern is expected given the construction: the achromatic block pools black, grey, and bright bins and absorbs a large share of pixels, so the leading source of variance in the simplex of color shares is a tonal (achromatic) versus warm-earth contrast. Importantly, this is not the signature of a simple fading mechanism. Varnish yellowing would mechanically raise the warm block and would therefore induce a smooth drift in the opposite direction, whereas the estimated indices display pronounced turning points

Figure B8: Blocked color indices and PC1 loadings across countries (six blocks)

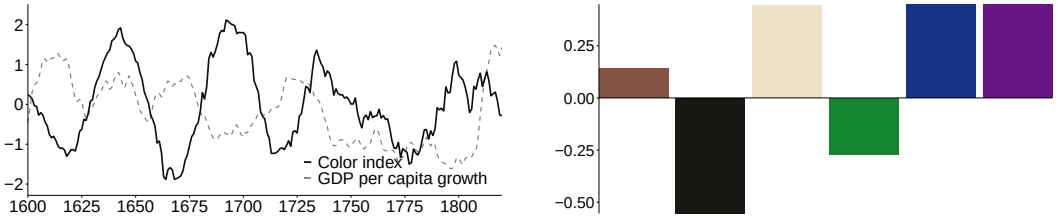
(a) Holland



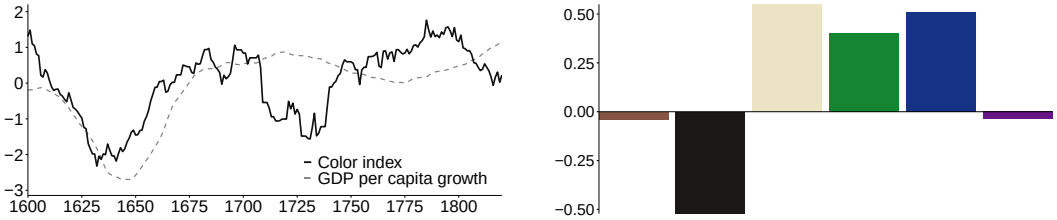
(b) France



(c) Italy



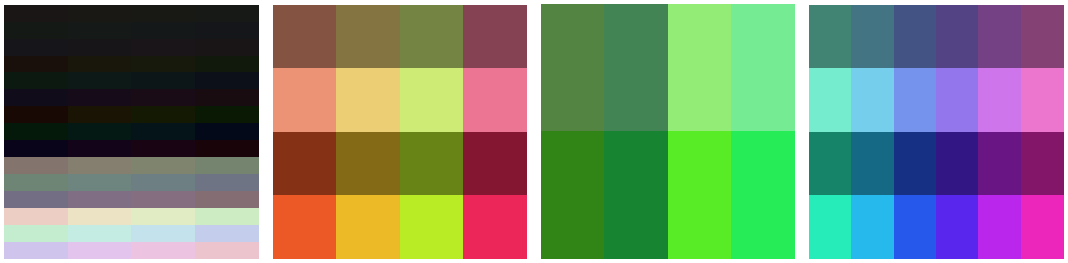
(d) Germany



Note: Left panels plot the blocked PC1 index; right panels show the associated PC1 loadings. All indices are constructed using the six HSV blocks in Figure B6.

and short- to medium-run fluctuations that align with benchmark growth. The four-block specification should thus be read as an "extra-robust" test showing that the main signal survives when fine hue distinctions are discarded..

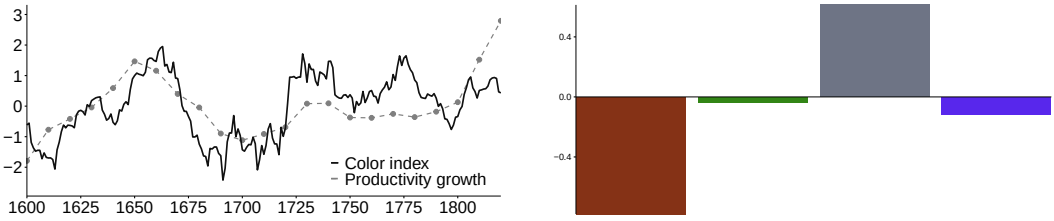
Figure B9: Four HSV color blocks used for the extra-robust recoding



(a) Achromatic (black/grey/white) **(b)** Warm (red/orange/ochre) **(c)** Green (yellow-green/green) **(d)** Cool (cyan/blue/purple/magenta)

Note: This recoding collapses the 108 HSV bins into four coarse families intended to absorb drift from yellowing and chroma loss. Tiles again show the underlying bins included in each block under the fixed HSV-to-HEX palette.

Figure B10: Great Britain: blocked color index and PC1 loadings (four blocks)

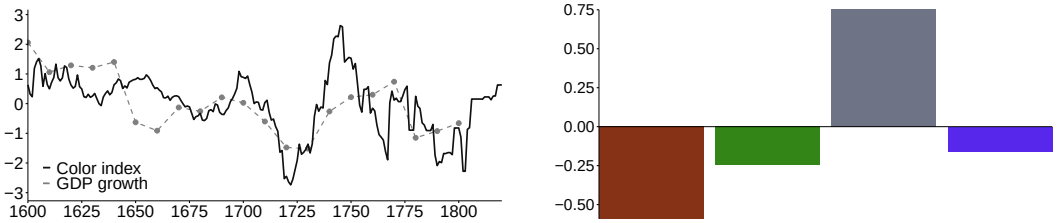


(a) Blocked color index **(b)** PC1 loadings on blocks

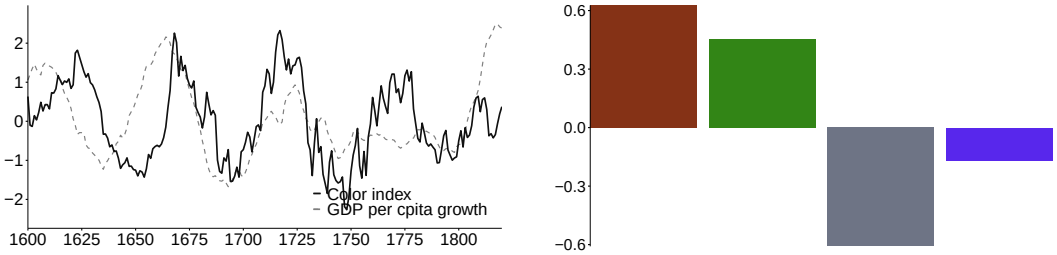
Note: Same estimation as Figure B7, but using the four-block aggregation in Figure B9.

Figure B11: Blocked color indices and PC1 loadings across countries (four blocks)

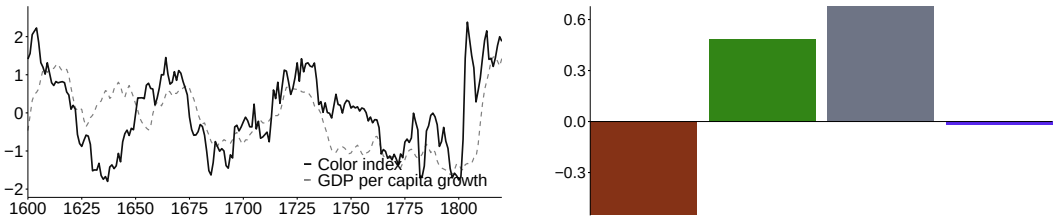
(a) Holland



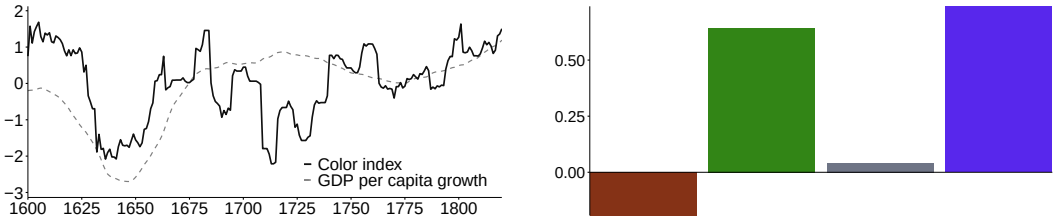
(b) France



(c) Italy



(d) Germany



Note: Four-block version of Figure B8. Left: blocked index; right: PC1 loadings on the four families in Figure B9.

C Validation Exercises

C1 Regression Using Population

To assess whether visual features extracted from paintings proxy local economic development, we link the WGA oil-painting sample to historical city population estimates. The dependent variable is the natural logarithm of city population from Bairoch, Batou and Pierre (1988), downloaded from Nunn and Qian (2011).

Each painting is georeferenced to a city and assigned to the historical population observation grid. In the retained population sample, the period index takes six values: 1500, 1600, 1700, 1750, 1800, and 1850. We aggregate painting features to city-period cells and estimate all models at that level. Cities observed in only one period are excluded, so identification comes from within-city variation across periods. Standard errors are clustered at the city level throughout.

Regressors are built from the 108 HSV bins described in the paper. Within each hue channel, bins are ranked by saturation and the most saturated bins are aggregated to form color shares. Darkest and brightest bins are reassigned to black and bright, respectively, because hue is weakly informative at value extremes. All features are winsorized, standardized, and rescaled to the unit interval to keep coefficient magnitudes comparable across color families.

Let i denote a city and τ a population period. For each predictor $x_{i,\tau}^{(m)}$, we estimate the following univariate interacted specification:

$$\ln\big(\text{Population}_{i,\tau}\big) = \alpha + \gamma_i + \delta_\tau + \beta_m x_{i,\tau}^{(m)} + \sum_{\kappa \neq \kappa_0} \theta_{m,\kappa}\Big(x_{i,\tau}^{(m)} \times \mathbf{1}\{\tau = \kappa\}\Big) + \varepsilon_{i,\tau}, \tag{C1}$$

where γ_i are city fixed effects, δ_τ are period fixed effects, and κ_0 is the omitted reference period under factor coding. For predictor m, the table coefficient corresponds to β_m, i.e., the slope in the reference period. In any non-reference period κ, the corresponding slope is $\beta_m + \theta_{m,\kappa}$.

$$\ln(\text{Population}_{it}) = \alpha_i + \delta_t + \beta_t \,\text{Color}_{it} + \varepsilon_{it}, \tag{C2}$$

Table C1 reports these city-level results for both the twelve-color system and the six macro-color blocks. The period grid used for estimation follows the Bairoch–Nunn population source.

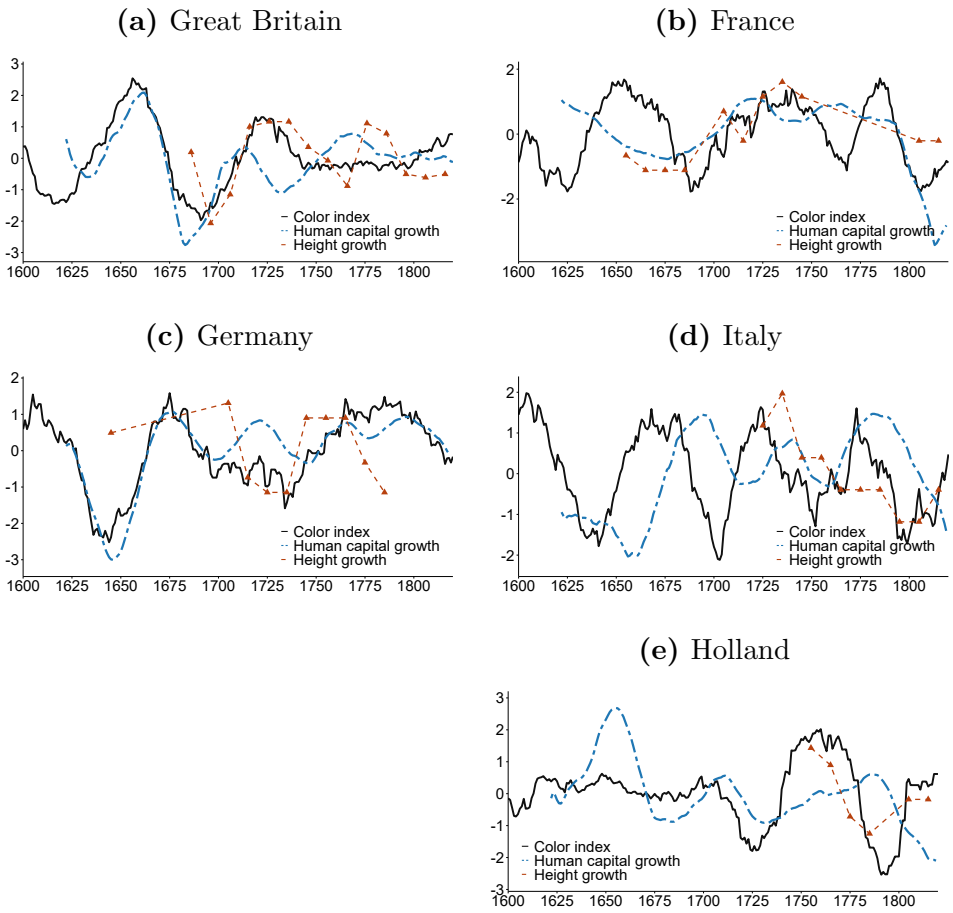
Table C1: Results Population

	Coefficient	Robust SE	p-value
Panel A: Color Shares (13 Color Families)			
Black	-0.56	0.622	0.367
Bright	1.32	0.873	0.134
Orange	0.02	0.857	0.978
Ochre	0.28	0.437	0.528
Yellow	0.37	0.605	0.547
Chartreuse	0.53	0.454	0.247
Green	-0.26	0.609	0.666
Azure	0.82	0.608	0.180
Blue	0.56**	0.245	0.023
Purple	-2.22	2.124	0.298
Violet	-2.42***	0.208	0.000
Pink	-2.29***	0.476	0.000
Red	-1.59**	0.784	0.045
Panel B: Color Shares (6 Color Families)			
Black	-0.21	0.339	0.545
White and Grey	1.38**	0.642	0.034
Warm	0.11	0.676	0.872
Green	0.37	0.650	0.572
Cyan and Blue	0.71**	0.338	0.038
Purple and Magenta	-2.23***	0.526	0.000
Observations		195	
Cities		64	
Periods		6	

Notes: Coefficients, robust standard errors, and raw p-values are reported in separate columns.
Significance stars are attached to coefficients and based on raw p-values.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

C2 Comparison with Human Capital and Height

Figure C1: Color Indices, Human Capital Index, and Height



*Note:*The figure compares the growth rate of the color-based index, the human capital index for universities, and height for Great Britain over the period 1600–1820. For comparability, and given its exponential trend, we use the detrended logarithm of each variable. All series are standardized to zero mean and unit variance for comparability. The color index summarizes annual changes in painting brightness and chromatic composition derived from the WGA dataset. For the detrended logarithm of the human capital index we compute the change between adjacent two-decade (20-year) windows, consistent with the rolling-differences approach in (1).

C3 HSV and Reality

C3.1 Brightness in Paintings, Albedo, and Weather Conditions

For testing the relationship between painting, albedo, and weather conditions, we construct the measure of albedo according to Duffie and Beckman (1980) and Iqbal (2012) and following the procedure contained in the Appendix of Ashenfelter and Storchmann (2010). Table C2 show the variables selected from the lasso among explanatory variables including seasonal precipitation, monthly albedo, and their interactions, controlling for season, month, longitude, latitude, year, and technique.

Table C2: Lasso Results

Dependent variable: Pixel Effective Brightness		
	Lasso	Post-est OLS
Winter Precipitation	-0.0963	-0.1346
$H_{0\beta\gamma}$_$February\times$ Winter Precipitation	-0.5484	1.4597
$H_{0\beta\gamma}$_$May\times$ Spring Precipitation	1.3158	5.1445
$H_{0\beta\gamma}$_$July\times$ Summer Precipitation	0.8243	0.7017
Latitude	0.1253	0.3895
Longitude	-0.0044	-0.1954
Constant	147.8912	137.4848
Number of observations	15,476	15,476

C3.2 Brightness in Paintings and Wine Sweetness

Table C3: OLS Regression

Dependent variable: Grape must sugar content						
Pixel brightness	0.05**	0.05**	0.01	0.00	0.01	0.02
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Year	-0.01	-0.02	-0.01**	0.01	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Latitude		0.06	0.08***	-0.03	0.14	-0.11
		(0.06)	(0.03)	(0.02)	(0.19)	(0.10)
Longitude		0.04	0.02	0.10*	0.37**	0.04
		(0.05)	(0.05)	(0.05)	(0.15)	(0.11)
Constant	-0.80	1.87	-4.54**	-4.01**	-11.50	3.88
	(2.49)	(3.28)	(2.09)	(1.64)	(9.94)	(4.85)
Country	Germany	Germany	France	Italy	Holland	Great Britain
Observations	188	188	847	553	601	178

Robust standard errors in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

C3.3 The Laki Eruption and the Darkness in the Painting

In this subsection, We study whether the 1783 eruption of the Icelandic volcano Laki is associated with a shift in the darkness of paintings produced around the event. We implement a before/after design in a narrow symmetric window of $K = 3$ years before and after the eruption year. This horizon is intended to proxy the short-run period in which volcanic aerosol and haze-related effects are most likely to matter for ambient light conditions and artistic production (Thordarson and Self (2003) and Zerefos et al. (2007)).

Let p index paintings, t_p denote the painting year, $c(p)$ its country, and $g(p)$ its genre/type. The outcome $\tilde{D}_p$ is the painting-level share of dark colors (constructed as the sum of pre-specified HSV bins). We define the post indicator as

$$\text{Post}_p = \mathbf{1}\{t_p \in [E,\, E + K - 1]\}, \quad \text{with } E = 1783,\ K = 3,$$

and restrict the sample to $t_p \in [E - K,\, E + K - 1]$.

Our baseline specification estimates the average change in darkness after the eruption while controlling for level differences across countries and types:

$$\tilde{D}_p = \alpha + \beta\,\mathrm{Post}_p + \gamma_{c(p)} + \delta_{g(p)} + \varepsilon_p. \tag{C3}$$

Here, β captures the mean difference in darkness between the post- and pre-eruption windows, conditional on country fixed effects $\gamma_{c(p)}$ and type fixed effects $\delta_{g(p)}$.

As a robustness check, we allow the post-eruption change to differ by country and by type by interacting the post indicator with country and type indicators:

$$\tilde{D}_p = \alpha+\beta\,\mathrm{Post}_p+\gamma_{c(p)}+\delta_{g(p)}+\sum_{c\neq c_0}\theta_c\big(\mathrm{Post}_p\times\mathbf{1}\{c(p)=c\}\big)+\sum_{g\neq g_0}\kappa_g\big(\mathrm{Post}_p\times\mathbf{1}\{g(p)=g\}\big)+\varepsilon_p. \tag{C4}$$

This specification tests whether the eruption is associated with heterogeneous changes in darkness across countries or genres. We repeat the analysis for alternative window lengths K as a sensitivity check.

Table C4: Darkness around the 1783 Laki eruption ($K = 3$ years pre/post)

Dependent variable: Share of dark colors (*share_dark*)		
	(1) Baseline FE	(2) FE + Post interactions
Post	0.075**	0.074**
	(0.032)	(0.030)
Country FE	Yes	Yes
Type FE	Yes	Yes
Post × Country	No	Yes
Post × Type	No	Yes
Observations	130	130

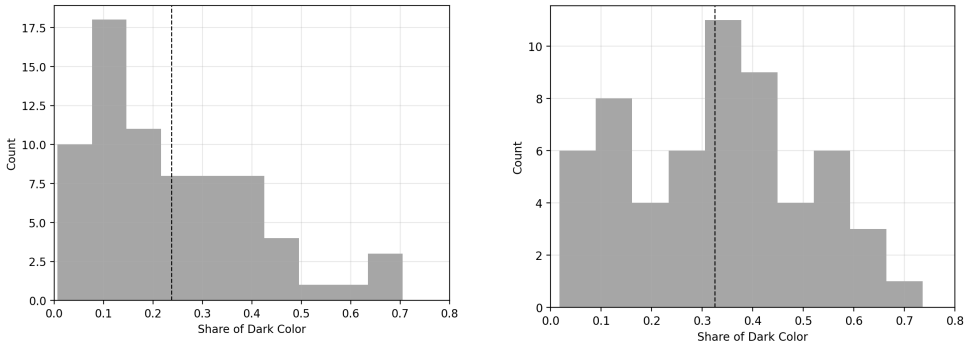
Notes: Robust standard errors in parentheses. The post period includes the eruption year (1783). Column (1) estimates a common post–pre shift controlling for country and type fixed effects. Column (2) allows the post shift to vary by country and type via interactions; the reported coefficient is the *average* post–pre effect implied by the interacted model (computed by averaging fitted post–pre differences over the estimation sample).

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure C2: Dark Color Shares Around the 1783 Volcanic Eruption

Panel A: Pre-eruption window (1780–1782)

Panel B: Post-eruption window (1783–1785)



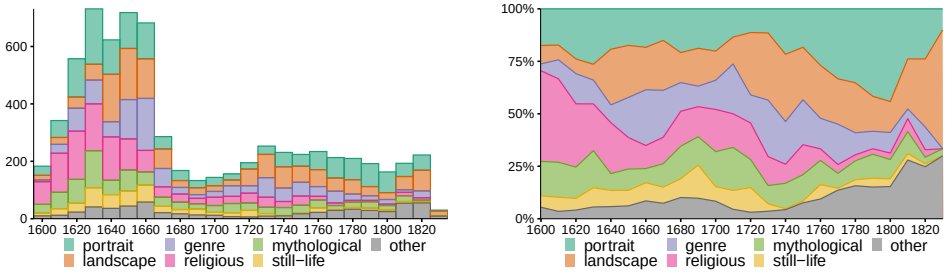
Note: The figure shows histograms of the painting-level share of dark colors for landscape paintings only. Panel A pools works dated to the ten years prior to the 1783 eruption (1780–1782), while Panel B pools works dated to the ten years after (1783–1785). Both panels use 10 bins. the vertical line displays the average. Average for panel A is 23.7%, average for panel B is 32.5%.

D Additional Figures

Figure D1: Paintings by Type Over Time

(a) Count by decade

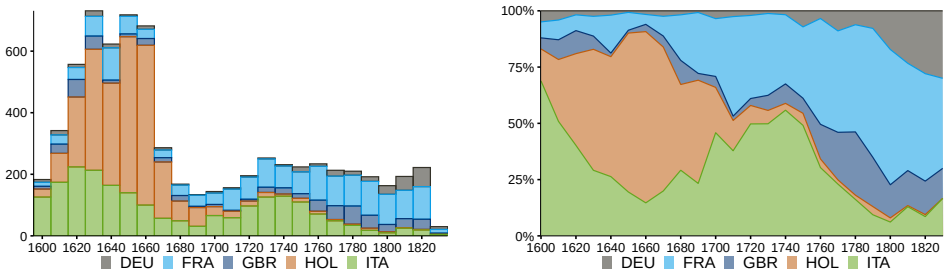
(b) Share by decade (100%)



Note: Time is binned to decades. The left panel reports the number of paintings per decade. The right panel reports each type's share within a decade (summing to 100% in each decade). Other includes also study type and historical type.

Figure D2: Paintings by Country Over Time

(a) Count by decade **(b)** Share by decade (100%)



Note: Time is binned to decades. The left panel reports the number of paintings per decade. The right panel reports each type's share within a decade (summing to 100% in each decade).

E The Economic Life of Colors

Building on the conceptual relationship between brightness and economic activity discussed above, we now turn to the chromatic dimension itself. The following subsections examine the seven principal hues of the visible spectrum – violet, indigo, blue, green, yellow, orange, and red – each reflecting distinct material, technological, and cultural conditions that together illustrate the economic life of color.

Violet

Economically, violet reflects both the extreme cost of pigment production and its role as a signal of concentrated wealth and social hierarchy. Historically, it was rarely used because its most prized pigments, derived from Mediterranean murex sea snails or from the combination of red and expensive blue minerals, were extraordinarily costly. Tens of thousands of snails were required to produce a small amount of dye, making it an exclusive and high-status color (Iluz, 2013). As Pastoureau and Simonnet (2005) document, violet had ambivalent associations depending on the region. In Catholic countries such as France and Italy, it was linked to Lent, mourning, and the Virgin Mary. In Great Britain, by contrast, it was tied to royal exclusivity, and Elizabethan sumptuary laws even reserved "royal purple" silk for the crown (Sylvester, Chambers and Owen-Crocker, 2014).

Indigo

From an economic perspective, indigo illustrates the tension between global trade integration and domestic protectionism. Although derived from exotic leaves imported from the West Indies, indigo was long regarded as an inferior substitute for ultramarine made from lapis lazuli (Pastoureau, 2019). In France, indigo gained prominence through its use in Napoleonic uniforms (Zieseniss and Le Bourhis, 1989) but faced resistance from woad producers, who viewed it as an imported competitor threatening their markets. Cultural opposition was reinforced by the unpleasant odor of fermenting leaves (Lotut, 2018).

Blue

Blue captures the interplay between trade, technology, and social meaning. Despite its wide presence in nature, blue pigments were historically rare because lapis lazuli, their primary source, was mined mainly in Afghanistan and Iran, which made extraction and transport extremely costly (Pastoureau, 2023a). From the twelfth century onward, especially in France, blue became associated with the Virgin Mary and later with civic and religious authority. It emerged as a symbol of stability and prestige, particularly in heraldry and royal ceremonies (Pastoureau, 1993). Protestant reformers, notably Lutherans and Calvinists, adopted darker blues to signal moral restraint.

Economically, the invention of Prussian blue in Berlin in the early eighteenth century, based on a synthetic, salt-derived process, transformed blue into a more affordable and exportable product. This democratized access to the color and shifted its symbolism. Yet shades mattered: lighter blues were linked to youth movements such as Wertherism, distinguished by melancholy and romantic despair, and even to moral decay. In English, the term *blue devils* referred to hallucinations caused by alcohol withdrawal. Thus, blue oscillated between elite symbolism and mass accessibility, reflecting underlying technological and cultural transitions.

Green

Green often functioned as a proxy for economic vitality and social mobility. As Pastoureau (2014) notes, its Old English linguistic root, *grōwan* ("to grow"), underscores its association with wealth and abundance. Since Roman times, green symbolized prosperity and peace, and throughout the Middle Ages it maintained positive connotations, except for certain greenish hues tied to toxic materials such as arsenic. Although medieval lore sometimes linked green to demons, witches, or poison, by the early modern period it had become the color of commerce and the bourgeoisie, as Goethe (1810) observed.

Exception: In the Netherlands, green acquired negative connotations and was condemned by Calvinist moralists as the color of frivolity and deceit. It was associated with gamblers, jesters, and parrots (Pastoureau, 2014).

Yellow

Yellow provides a striking example of how abundance can turn to stigma. Though historically easy to produce from ochre and shells, its meaning shifted from solar power and wealth to deceit and exclusion. As Goethe (1810) described, it could be "gay and joyous" but quickly became "dirty and uninteresting." Its association with bile and humoral medicine during the Middle Ages linked it to envy, madness, and treachery (Pastoureau, 2019). By the seventeenth century, yellow had been marginalized in both fashion and heraldry, replaced by gold or red.

Exceptions: In France, yellow retained a positive aura due to ideals of blond beauty celebrated by medieval *troubadours*. In Italy, yellow continued to appear in sacred paintings, sometimes replacing gold tones to signify sanctity and divine light.

Orange

Orange marks the intersection of globalization and identity. As Pastoureau (2019) notes, it was not recognized as a distinct hue in Europe until the introduction of citrus fruits from Asia. Its pigments, derived from campeche wood and brazilwood, depended on colonial imports and were therefore scarce. Con-

sequently, orange shared much of red's symbolism until the sixteenth century, when it began to carry its own meanings of warmth and dynamism.

Exception: In the Netherlands, orange gained unique political and cultural status through its association with the House of Orange. It became a symbol of Protestant identity and civic pride, often replacing yellow in fashion and national iconography.

Red

Red illustrates the transformation of a ubiquitous, inexpensive pigment into a moralized and regionally differentiated symbol. Before 1500, it was the most common color in both art and dress, associated with vitality, blood, and fire (Pastoureau, 2023b). Its production from plants and insects made it cheap and accessible. After 1500, however, red declined for several reasons: the growing popularity of blue, the Reformation's rejection of ostentation, and the Catholic Church's replacement of red with white in its rituals. Newton's decision in 1666 to place red at the end of the spectrum symbolically reinforced this marginalization.

Exceptions: In the Netherlands, red maintained positive connotations due to access to luxury pigments such as Mexican cochineal and sandarac, used by painters like Van Eyck and Rubens (Pastoureau, 2023b). Similarly, in France, bright red and pink tones derived from brazilwood became fashionable in the eighteenth century, promoted by figures such as Madame Pompadour (Pastoureau, 2025). These localized preferences reflected both trade access and the cultural politics of refinement.