IMAGE(S)∗

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Abstract. From clothes and hairstyles to fashion accessories, humans use a great range of stylistic elements to express themselves, impress others, demonstrate their individuality, or show that they belong to a group. Despite its central importance as a form of social interaction and self-expression, and a rich body of theoretical work, empirical work on fashion and style choices is rare. We present new methods to use images as a high-frequency, granular source for the analysis of cultural change. We measure similarity over time and space, tracking the timing and location of influential style innovations. To illustrate our methods, we systematically exploit data from more than 11 million high school yearbook pictures of graduating US seniors to analyze persistence and change in style. We use the arrival of the Beatles in the United States in 1964 as a case study to demonstrate the potential of image analysis to detect cultural innovation and diffusion.

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The image we project, the style we chose, the clothes we wear, the haircut we have, and the glasses we pick reflect personal preferences. Do I express my individuality, and decide to look completely different from anyone around me? Do I wear the same suit and tie as everyone else? Every one of us, every day, makes choices of personal style. But the clothes we wear and the styles we pick are not only driven by personal preferences. They also reflect society-wide trends (Hancock, Johnson-Woods, and Karaminas 2013). Firms launch products (Pesendorfer 1995), images circulate in the media, and millions of individual, everyday choices jointly determine the visual culture of an age. At any given time, the choice-set is limited. Some of these limits are formal: Many religions closely circumscribe what is considered acceptable dress, especially in the case of women; sumptuary laws routinely determined which groups in society were allowed to wear what (Riello and Rublack 2019). Other restrictions reflect social norms: Is it permissible to deviate from what others wear? Can a man have long hair, a woman short hair? Do men wear wigs or tights?

Stylistic choices are part of everyday culture. Culture often persists over long periods, with everyday practices reflecting economic incentives and cultural factors centuries ago (Guiso, Sapienza, and Zingales 2016; Alesina, Giuliano, and Nunn 2011; S. O. Becker et al. 2016). At the same time, it can also change rapidly. Attitudes towards pre-marital sex, smoking, homophobia, and racial views have been transformed in many Western countries in recent decades (Fernández, Parsa, and Viarengo 2019; Giuliano and Nunn 2021). One key challenge in the analysis of cultural change is a lack of high-frequency, granular data. Survey measures often use relatively small samples, and disaggregation to the state or local level reduces cell size still further. Another challenge is the lack of consistent measurements. In many models of group behavior (Kuran 1989; Chamley 2004), waves of change can be initiated by a few individuals. What is missing in the analysis of cultural change is a consistently measured, high resolution indicator that is observed with sufficient frequency over time and space. While recent research has made important progress analyzing themes in folk tales (Michalopoulos and Xue 2021) or using surveys to measure rates of time preference (Sunde et al. 2022), we still lack good indicators of cultural change for most periods and countries.

In this paper, we introduce a new source to measure cultural innovations at high frequency and at the granular level, exploiting a rich dataset of High School senior images. We develop methods to analyze both persistence and conformity in portraits, and apply them to the case of the US, 1940-2010. Looking at a single country in the more recent past is motivated by several considerations: Since time immemorial, sumptuary laws regulated who is allowed to wear what; it is only in recent centuries that individual choices without formal restrictions become a dominant factor in fashion. This leads us to focus on the more recent past. The advent of photography greatly facilitates access to accurate representations of actual clothing and hair styles. Arguably, the US was at the forefront of cultural change in the second half of the 20th century. Its size and diversity allow for meaningful cross-sectional analysis. We focus on high school senior images for reasons of data availability, and because they capture

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1 For example, in the GSS, some questions are added from wave to wave, while others are dropped.
how students chose to portray themselves to others (and posterity) at an important inflection point of their lives – when their secondary education comes to an end, and they either go off to college or join the labor force. US high school yearbooks are typically sold to the entire student body and have high sentimental value.

To demonstrate the usefulness of this new data source and of the methods we develop, we present three case studies. First, we examine the rise and fall of conformity and persistence in styles over time in the US. Within each graduating high school class, we examine how different styles are, and document the timing, speed, and location of the decisive changes that began in the late sixties, following the Woodstock festival and the “summer of love” in 1968. We show that counter-culture – defined as a low level of conformism and low persistence of styles vis-à-vis the parent generation – peaked in the mid-seventies. Since then, many of these trends have reversed, leading to more conformity and growing persistence.

What does our new data say about the arrival of new trends? Which ones “go viral” and which ones flop? We draw on recent work in the economics of innovation (Kelly et al. 2021) to create a measure of influential innovation. For the case of California, we examine where such innovation occurred, and show that innovation is most pronounced in major cities. We observe San Francisco as an epicenter of style innovation in the early 70s, in keeping with its role as a focal point of counterculture in the late 60s.

In our third application we explore whether our methods and source can be used to document and trace the impact of a single, major event that is widely credited with changing US visual culture – the arrival of the Beatles in 1964. While still largely unknown in 1963, the Beatles appeared four times on the popular CBS Ed Sullivan show in the spring of 1964. They immediately vaulted to the top of the charts, and “Beatle-mania” swept the US. Popular commentary focused as much on the group’s hair style as on their music. We train a classifier to detect the particular hair style in our images. In the same year as the broadcast, the areas close to CBS stations, the share of men who sport the Beatles-style look in their senior portrait jumps, but stays constant elsewhere. Areas served by other TV stations show no significant jump. After 1964, the mean probability of a Beatles-style “mop-top” starts to rise everywhere; within a few years, the mean probability of a “mop-top” hairstyle increased by 25 pp, suggesting that lots of high school seniors had adopted the hair style of the Fabulous Four from Liverpool.

Interest in using photographs and regularities in appearance as a source for social science analysis dates back to the 19th century. A few decades after the invention of photography, Francis Galton (Galton 1878) famously sought to identify the typical facial characteristics of criminals, mentally ill, and prostitutes by superimposing multiple portrait photographs. Systematic analysis of images in computer science has taken off in the last 20 years. For example, Hidayati et al. (2014) analyze fashion trends based on New York fashion week couture based on a classification algorithm, and Lee et al. (2015) extract information on agricultural trends from images. Along

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2 Ginosar et al. (2015) apply a similar approach to contemporary student portraits, and examine the display of emotions over time.
similar lines, Kiapour et al. (2014) create five main clothing style categories from human coding and roll out a categorization scheme based on models trained on these classifications.

Our paper is the first to use a large sample of images as a source for analyzing cultural change. We do so through the lens of fashion. Analyzing fashion as an indicator of social change has a long lineage. Theodor Veblen (1973) famously analyzed conspicuous consumption as a marker of social distinction. Georg Simmel’s (1957) essay about the “Philosophy of Fashion” already emphasized how adopting particular styles was mostly about conveying one’s own position, standing, and taste: “Judging from the ugly and repugnant things that are sometimes en vogue, it would seem as though fashion were desirous of exhibiting its power by getting us to adopt the most atrocious things for its sake alone.” Economic analysis of fashion goes back to the classic work by Leibenstein (1950), who differentiated between “snob” and “bandwagon” effects, with adoption becoming either more or less likely as a function of others’ adoption decision and type. Becker and Murphy (1993) derive a microfounded model of such consumption externalities. Matsuyama (1991) explicitly models groups of conformists and non-conformists, and shows that demand for goods can fluctuate cyclically (“fashion cycles”). Imitation of first-movers in consumption is also prominent in Banerjee (1992), while Karni and Schmeidler (1990) present a model of social stratification in consumption. While there is no shortage of theoretical papers in economics analyzing the diffusion of fashion as a social phenomenon, there is little empirical work on the origins, spread and similarities of style and fashion over time and space.

1. History and Background

Portraits and photography. Clothing and jewelry are probably as old as mankind. Early pre-historic art depicts skirts and animal skins, dresses, and different hairstyles (Bigelow and Kushino 1979). Accessories have been unearthed by archaeologists for periods as far back as the 16th century BC (Nosch, Michel, and Harlow 2014). While styles came and went in many locations and periods, rapid changes in preferred or acceptable clothing and hairstyle – fashion – is probably a relatively recent phenomenon. Braudel (1975) famously argued that rapid changes in dress originated in Europe, among the upper classes during the late Middle Ages, as a way to distinguish themselves from the lower orders. This view is controversial and undoubtedly euro-centric; fashion and periodic, if not necessarily rapid, change in dress is probably as a human universal (Welters and Lilletun 2018).

Industrialization coincided with the spread of textile manufacturing, especially of cotton (Crafts 1985). As productivity surged and the cost of new cloth fell, fashion items became more widely accessible. Some historians have located a “consumer revolution” in 18th century English society, centered on new fashions. McKendrick, Brewer and Plumb (1982) argue that even servants could afford several fashion accessories every year, making it easier to follow new trends – and creating a greater need among the upper classes to distinguish themselves.
Forms of presenting oneself to others and posterity also date back to antiquity. Kings and emperors had their faces depicted on coins and on marble statues. Popes, kings, and officials down to early modern burghers commissioned portrait paintings of themselves, showing themselves as warriors or in the stark simplicity of black robes, in front of their worldly possessions or with family, friends, and favourite pets. Many famous artists painted self-portraits (Carbon 2017), from Dürer to Picasso, presenting everything in every style from darkly realistic images to idealized versions of themselves (Beyer 2003).

The arrival of photography changed the extent to which images could be embellished. At the same time, it created new scope for highlighting one’s preferences and individuality, from the style of photograph chosen to the manner in which one dressed and presented oneself to the world. The very first portrait pictures date back to 1839; by the 1840s, daguerrotypes had become common. From the 1930s, roll film allowed a quantum leap in the mobile use of cameras, and brought costs down; soon, family outings and celebrations were not complete without an – often staged – picture commemorating the occasion (Prodger 2021).

High school yearbooks became popular in the US from the 1930s; by the 1940s, many high schools compiled annual overviews depicting every student, ordered by class. The yearbooks would also describe events as well as depicting teachers and sports teams.

Post-war American culture and 1968. As the country emerged triumphant from World War II, American culture exerted a strong influence around the world. Hollywood, American TV shows, American universities and music combined into a powerful and seductive form of “soft power”. Youth rebellion against established norms became a dominant and recurring theme in fashion and an important form of self-stylization.

Growing economic prosperity and rapid demographic expansion were accompanied by a cultural revolution, particularly among young people, who began to challenge traditional social norms and values. In the 1950s, teenagers began to embrace rock ‘n’ roll music and a more rebellious teenage culture. This led to the rise of a youth counterculture in the 1960s, which was marked by a rejection of traditional values and the embrace of a more liberal lifestyle. The youth rebellion of the 1950s and 1960s had a profound impact on American culture. While creating frictions in civic society, and between old and young, some observers argue that it ultimately led to a more tolerant and diverse society.

The counter-culture of the 1960s centered around three main themes – opposition to the Vietnam war, rejection of traditional social and sexual mores, and the use of psychedelic drugs (Issitt 2009). While in some ways similar to the earlier Beatniks, the counter-culture of the sixties is a distinct cultural phenomenon. Hippies and anarchists like the Hells Angels made their rejection of traditional society clear in many dimensions, but their physical appearance(s) was often what shocked older observers the most. Men would wear their hair long; facial hair made a comeback; many hippies cultivated a deliberately casual look, some even refusing to wear shoes. Hand-printed
shirts and skirts in psychedelic colors were common, as were long flowing dresses for women.

Hippie style and culture largely originated with middle-class youth. They came to diffuse widely in society, possibly because its torch-bearers were ethnically, culturally and in terms of social status, close to the mainstream (Davis 2013). By the late 1970s, many stylistic elements of the counter-culture had become “normal” (Kopkind 1979). To provoke required something new, like the mohair, leather and spike style of punks. Nonetheless, influential innovation in the 1980s and 1990s never reached the levels of the 1960s and 1970s.

2. Data

American high school yearbooks have a long lineage. From the early 20\textsuperscript{th} century onwards, student associations began to publish annual yearbooks containing a range of information on clubs and societies, events and sporting competitions. Initially focused on collecting memorable utterances of seniors for the enlightenment of juniors, these quickly evolved into a collection of portraits of students. By the 1930s, a high share of American children attended high schools, and a high share of them published yearbooks containing portraits. Figure A.1 gives an example of such a publication from 1959, for Tift High School in Tift, Georgia. Most images are relatively small, and only portray the head and upper torso. Black-and-white pictures give way to color from the late fifties onwards.\(^3\) Most pictures are frontal or \(\frac{3}{4}\) frontal portraits; pictures in profile are rare.

While a range of different sources exists, the commercial website www.classmates.com has by far the most comprehensive collection. For the period 1930 – 2010, it contains a total of over 350,000 yearbooks. Classmates.com already covers thousands of high schools in 44 states from 1930 onwards. This number increases further into the 1980s.

We first run a portrait recognition algorithm to identify where in a yearbook pictures of students are displayed. It scans for faces and a sequence of rectangles on the page, with a darker border compared to the background. We identify sections with seniors by using a symbolic algorithm to decide where the section for seniors begins. To this end, we look for at least four pages of consecutive images of similar size and color mix. We also require the word “senior” to be at the start of the section, and exclude all sections containing the words “junior”, “faculty”, or “teachers”. We also use information on color and size to identify senior images (which are more likely to be in color and often larger). Human audit samples suggest that we have about 5\% false positives, and identify about 70\% of all available senior portraits correctly.

We use two main datasets for our analysis. First, we create a balanced panel without sacrificing broad geographic coverage (US Sample). To do so, we rank yearbooks in each city by coverage – the number of yearbooks between 1930 and 2010. Within each city, we also rank high schools by the coverage of the corresponding yearbooks. For each of the top 25 cities acc. to this ranking, we use the three

\(^3\) To avoid this influencing our results, we convert all pictures to black-and-white.
yearbooks with best coverage. The benefit of this sampling approach is that less of the
variation over time is the result of new schools coming in or dropping out of the
sample. Figure A.2 shows the number of high schools covered by the data as well as
the total number of available images.

For the second sample, we draw from the entire universe of yearbooks; for the
purposes of this working paper, we only utilize this data for California.

3. Methods

Humans can typically judge the similarity of images instinctively and quickly (Ginosar
et al. 2015). Consider Figure 1. On the first row is a selection of 1964 yearbook images
from Natick High School, Massachusetts. All the young men wear jackets, white shirts,
and black ties; all have short hair and no moustache. Their facial expressions, while not
identical, are broadly similar – somber, confident, serious. Now consider the second
row, from the same high school in 1984. Two of the men have long hair, two short hair.
One wears suit and tie, two a t-shirt and one an open shit. One sports a moustache,
the others not. Looks range from defiant to absent-minded or gazing into a far
distance.

While the human eye processes these differences rapidly and half-consciously, a
systematic approach to image similarity requires an algorithm that can capture most of
these differences quickly and reliably. Analyzing and classifying images is an important
challenge in computer science. To compare styles, we need a metric that allows us to
measure the style attributes of individual portraits. There are two broad approaches –
analysis of features captured by the image, or direct comparisons of image features and
attributes like the color or brightness of pixels, individually and collectively, which is
then often translated into a quality score. In the second approach, quality measures of
two images are then compared through measures such as the structural similarity index
measure, SSIM (Wang et al. 2004).

We focus on the analysis of style vectors – combinations of individual, identifiable
features. To this end, we first define a style vector of N characteristics, specific to each
portrait, $A = \{a,b,c,...,N\}$, where $a$, $b$, $c$... are style attributes chosen. Figure 2 gives an
overview of the composition of styles in our sample for men. In the 1940s, around 70% of
men were in the same group – suit, tie, shirt with a collar, no glasses, short hair, no
jewelry, and were clean-shaven (style 221). Another tenth had glasses and facial hair,
but shared all other attributes (style 222 and 223). Another 10-15% had short hair, no
suit, no tie, shirt, no facial hair (style 241). Four styles alone account for 90% of the
sample in most years. Style 221 declines in the 1950s already, and men with suits and
bow ties become more common. By the late sixties, the influence of the most
traditional style (221) falls sharply, from a share of 60% in 1966 to less than 10% by
the mid-seventies. Some its use is taken over by pre-existing styles, but the share of
“other” (style 999) increases sharply, accounting for more than 30% of the sample by
the late seventies. Suit and tie, combined with a moustache, enjoys a brief moment as
the dominant style in the 1980s. The more informal shirt without a collar, short hair,
no tie style (265) becomes the most common combination by the 1990s. It is striking
that “other” (style 999) is the most common type in our sample by the 1970s already, and outranks the proportion of any single style – a sharp change from the 1940s and 1950s, when less than 10% of high school seniors were in this category. In other words, fragmentation of styles increased sharply over time – from a minority of each class that fell outside the top few categories, to the largest single group.

We are interested in analyzing conformity and persistence – the extent to which individuals in a group “stand out” relative to their peers at any one moment in time, and the degree to which they look like their parents. Complete conformity would imply that everyone picks the same action, for example \( A = B = \{ 2, 2, 2, 2 \ldots 2 \} \). By contrast, individualism implies a high degree of individual expression: \( A = \{ 2, 2, 2, 2 \ldots 2 \} \) and \( B = \{ 52, 2, 932, 1, \ldots, 177 \} \).

When persistence is low, there will be little overlap in the styles chosen in the two periods – for example, \( A_t = \{ 99, 88, 77, \ldots, 99 \} \) and \( A_{t+1} = \{ 33, 21, 1, \ldots, 911 \} \). A highly conformist society can also show a great deal of persistence and stability over time: \( A_t = \{ 2, 2, 8, 2 \ldots 2 \} \) and \( A_{t+1} = \{ 1, 2, 2, 2 \ldots 2 \} \). We use cosine similarity as the main indicator of style differences

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\cos(\theta) = \rho_{AB} = \frac{A \cdot B}{||A|| ||B||}
\]

where \( A \) and \( B \) are vectors of style attributes. Cosine similarity ranges from 0 to 1; two images that share no characteristics score 0, and identical ones, unity. Cosine similarity is useful for our purposes because it is designed to capture relative differences between pairs rather than making absolute comparisons.

We use a sparse vector of image characteristics to robustly capture the style of high school seniors in our sample. The vector should be long enough to span the overall set of possible forms of stylistic expression; it should be sparse enough to be robust and allow for reliable identification of style attributes. To this end, we focus on a) tie (no tie, tie, bow tie), b) glasses, c) facial hair, d) jewelry, e) long hair, f) shirt with or without collar, and g) suit as style attributes. This results in a total of 191 possible combinations (for men) and 192 for women. Human audit samples suggest that we achieve accuracy in the 70-99% range for most characteristics (facial hair=70%; glasses=99%), with a majority of features in the 90+% range (gender, hair, tie, glasses, jewelry).

4. Applications

Measuring cultural change and persistence. We first present broad patterns of change over time and space, using the dataset of cities with the best data coverage during the period 1930-2010. We examine how similar a randomly chosen High School student is to other individuals from his or her class (“individualism”). We also repeat the exercise by comparing each student in year \( t \) with people graduating from the same high school 20 years earlier (“persistence”). Figure 3 plots the cosine similarity scores for both types of analysis over time.
We find a high degree of persistence, and low levels of individualism, for most of the 1950s and 1960s. Individualism levels show an inflection point in 1963/4 and begin to rise at an accelerating rate thereafter; from the early to mid-70s, they increase rapidly. Persistence stays relatively high until the late 1960s, before plummeting from 1970 onwards. Since the mid-1970s, individualism is gradually declining, and persistence has been creeping up. While levels of persistence are still far from those seen in the 1950s and 60s, individualism by 2010 had declined to levels close to those seen in the mid-1950s.

What stylistic changes drove the collapse of the conformity equilibrium in the late 1960s, and the triumph of individualistic expression and style diversity in the early 1970s? To examine the contribution of individual factors, we use LASSO regressions. LASSO modifies standard OLS regressions by means of a regularization that shrinks the coefficients of less important variables to zero (Mulhainathan and Spiess 2017). It is especially useful when dealing with high-dimensional datasets with many correlated predictors. Mathematically, it chooses $\beta$ so as to minimize the loss function given by:

$$R(\beta) = \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$  \hspace{1cm} (2)

where the first term penalizes the lack of accuracy and the second term penalizes the introduction of new covariables. Lambda ($\lambda$) is a hyperparameter and it is chosen by cross-validation, using the root mean squared error (RMSE) to assess prediction performance. It controls the strength of the penalty and determines the degree of sparsity in the model. As $\lambda$ increases, the penalty on the coefficients also increases, causing more of the coefficients to shrink towards zero. This results in a model with fewer predictors, which can improve the interpretability and stability of the model. If $\lambda = 0$, the LASSO estimator is equivalent to OLS.

We regress the dependent variable (individualism/persistence) onto the vectors of styles using the LASSO technique for each decade, at the individual level. Note that if a coefficient is not shown for a variable, it was shrunk to zero (for example, the contribution of facial hair to persistence in Figure A.4). Given the number of different styles, it could be that only a few of them are driving persistence and individualism. After penalizing for adding more variables, in most of the cases all styles survive (i.e. regularization parameter $\lambda$ is greater than zero). This reflects that the style characteristics we chose are “important” to some extent, i.e. have predictive power.

Some variables are clearly more important than others. Moreover, differences between the coefficient for a variable across the decades reflect that a particular feature can be more important in some decades that in others. Figure 4 plots the coefficients of LASSO regressions explaining the contribution of individual style characteristics to the overall individualism score of an image. Take the case of ties, for example. In the 1950s, 60s, and 70s, wearing a tie reduced a young man’s individualism score – it made him more similar to another, randomly chosen classmate. By the 1980s, this effect had declined markedly, and then reversed in the 1990s – US students graduating in that decade, and having their portrait taken with a tie, were more individualistic, meaning
their choice of this particular style attribute made them stand out more. Other factors underwent similarly striking changes over time. Long hair, for example, contributed the most to individualism scores in the 1970s. In contrast, glasses are always positively associated with greater individualism, and their effect is fairly constant across the decades.

In Figure 5, we examine persistence over time more closely. Instead of the (arbitrary) 20-year horizon used in Figure 3, we explore the similarity of high school portraits at different horizons. Darker colors show greater persistence; light colors indicate great differences. On average, longer horizons are associated with lower similarity. Until the cultural revolution of the early 1970s, similarity scores as far back as 15 years earlier were still positively associated with the style of seniors graduating from high school.

With the sharp rise of counter-culture in the 1970s, this changes profoundly. Similarity scores become zero or negative, indicating a radical decline in persistence. The discontinuity following the hippie movement is so profound and long-lasting that it is not before the mid-1990s that we detect substantial similarity from one generation to the next. In other words, it is only when the first cohorts affected by 1968 become the comparison group for contemporary high schoolers that we find evidence of persistence.

**Innovation and influence in style.** How can we tell if a style or fashion is genuinely new? And what innovations stick and propagate – and which ones wither on the vine? In our second example of using images as a source for detecting the changes in culture, we apply a simple methodology. It was recently developed for the analysis of US patents and their importance (Kelly et al. 2018). Here, we show how it can be adapted to document and measure how original and influential “innovations in style” are. Kelly et al. (2018) first calculate “backward similarity” as

$$BS_j^\tau = \sum_{i \in B_{j,\tau}} \rho_{j,i}$$  \hspace{1cm} (4)

Where $\rho$ is the cosine similarity between the vector of image characteristics for individual j and individual i belonging to the set $B$ of those who lived up to $\tau$ years earlier. In other words, backwards similarity captures how similar the looks of individual j are compared with all other individuals living between the present time t and t-$\tau$.

The second step in the Kelly method is to calculate forward similarity, defined analogously as

$$FS_j^\tau = \sum_{i \in F_{j,\tau}} \rho_{j,i}$$  \hspace{1cm} (5)

Where $F$ is the set of individuals living up to $\tau$ years in the future. The measure of image and style innovation of individual (or class) j is then simply
$$q_j^* = \frac{FS_j^*}{BS_j^*}$$

(6)

To fix ideas, consider two cases of style innovation: A young man or woman in 1961 may have chosen a style that is very different from anything that we can find in yearbooks in the preceding 30 years – BS would be low because the cosine similarity of his/her style with that of other people is low. But if FS – the extent to which people in the future look like him or her – is also low, q would be low. We consider this a case of “failed innovation”, a novel style that failed to catch on. On the other hand, men with long hairs, round sunglasses and scruffy beards in 1961 yearbooks would receive a low BS rating (they are different from the past), but a high forward-looking score because they look like many high school graduates in their own future (in this case, the late sixties and early seventies). Their q-score would hence be high – their deviation from the 1961 “norm” would be rated as important using this method because their style was both novel, and because it was picked up in the future. As in the original Kelly et al. paper, we only use a subsample of images to reduce computational complexity. The computational details of this innovation index are described in Appendix II.

In contrast to the Kelly et al. approach, which considers the entire future and past for patent innovation, our main measure only examines a five-year window looking backwards and the same span looking forward. The reason is conceptual: While a patent in year t might be influenced by an innovation at t-50, in terms of personal style, this is exceedingly unlikely. We demonstrate the robustness of our findings in the appendix.

Figure 6 shows the Kelly et al. measure over time. It is relatively flat and low in the fifties, and then declines during the early- to mid-sixties. Then, in the late sixties and early seventies, there is a lot of influential innovation – radically different from what came before. Backward similarity falls first, before forward similarity takes off in the mid-seventies. Influential innovation stays high throughout the 1970s, the most long-term influential period of style innovation in our data. While from the late seventies, high-school portraits start to look more like the past once more, forward similarity reaches new heights in the eighties, indicating influential innovation that is picked up in the nineties and naughties.

Next, using the q-score metric, we can examine which areas of the US were “culturally leading” – innovating and being ahead of the curve – and which areas were cultural followers, imitating the innovations of the leading areas years later. Since California has long been considered “ground zero” of the Sixties hippies movement, we analyze yearbook pictures from its main metropolitan areas. Figure 7 shows a heatmap of important innovation by area. There is substantial variation over both time and space. Panel A shows the centers of important innovation in California during the period as a whole. Unsurprisingly, San Francisco and LA stand out as centers of new style. Panel B shows the pattern of innovation in the Bay Area in 1970; Panel C does so for 1980. Here, we can see drastic changes. By the late Sixties, San Francisco becomes the area with the highest scores of the California sample – coinciding with the

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4 We use 25% of all available images for California, and 10% for the rest of the country.
rise of the hippie movement and the influence of the Haight-Ashbury scene (Cottrell 2015). This dominance does not last; by 1980, Oakland and San Jose have become more important centers of innovation.

“\textbf{You say you want a revolution.}” Can our data detect rapid cultural change? In this application, we examine one of the most famous cultural events in recent history – the Beatles’ arrival in the United States. Booked for the CBS Ed Sullivan show, the band appeared three times in February 1964, and once more in 1965. Their fame in the US had started to grow in 1963; the show is widely credited with creating “Beatlemania”. The broadcast’s audience numbered 73 million viewers, a record at the time, and more than three times higher than for an ordinary Sullivan show. Within a month of their appearance, the Beatles sold 2.5 million records; by April, their singles occupied all the top 5 spots in terms of record sales.\(^5\)

The press commented almost as much on the band’s hairstyle as on their music. All four musicians sported similar front-combed “mop top” hair. Beatles wigs copying the hairstyle were selling in their thousands per week (Mulligan 2010). In the US, just as in England, “the ‘mop top’ haircut became the new fashion style for teenage boys” (Loker 2009). In retrospect, it is hard to appreciate how much of the group’s novelty centered on their hair style, not their music. Paul McCarthy observed (Roylance 2000):

“We came out of nowhere with funny hair, looking like marionettes or something. That was very influential. I think that was really one of the big things that broke us – the hairdo more than the music, originally. A lot of people’s fathers had wanted to turn us off. They told their kids, ‘Don’t be fooled, they’re wearing wigs.’

A lot of fathers did turn it off, but a lot of mothers and children made them keep it on. All these kids are now grown-up, and telling us they remember it…. I get people like Dan Aykroyd saying, ‘Oh man, I remember that Sunday night; we didn’t know what had hit us – just sitting there watching Ed Sullivan’s show.’ Up until then there were jugglers and comedians like Jerry Lewis, and then, suddenly, The Beatles!”

While some believe that the Beatles’ success owes more to broad societal trends and chance than to their unique style of music and fashion (Sunstein 2022), we can examine how much of a discontinuity their arrival on the American musical scene made.

We first train a model to identify the fringe/“mop top” hairstyle, using 4,061 hand-coded images for training. The model achieves an overall accuracy of 83%. Looking at the sample of cities with long-coverage yearbooks, we show the evolution of Beatles-inspired hairstyles over time in Figure 8, panel A. We take the last year before the Beatles’ arrival on the Ed Sullivan show (1963) as our baseline, and plot

\(^5\) We thank Leonardo Bursztyn for inspiring this analysis.
coefficients of the likelihood of a mop-top in each year, distinguishing areas with and without CBS TV reception. There is a clear trend break after the Beatles’ appearance on the Sullivan show – prior to 1964, the trend is flat, and two years after their show, aggregate probabilities of Beatles-style hair have risen by 10 pp.

Interestingly, we find suggestive evidence that the CBS appearance was behind this aggregate trend break. The only areas showing a significant increase in the year of the show are those where CBS was broadcasting. Panel B explores this link further, plotting the probability of a mop top against distance to the nearest CBS station. For 1963, there is not link between fringe-style hairdos and distance to CBS; for 1964, this changes dramatically, with much higher rates near the CBS stations. In panel C, we show that in 1963, overall distributions of Beatles-style hair are identical in the CBS and non-CBS areas; in 1964, this is no longer the case, with low probabilities declining sharply and medium-to-high probabilities (40%+) rising sharply.

In Table 1, we examine the statistical significance of our finding. We use our data in a simple difference-in-difference framework, comparing areas exposed to CBS-programming to those that are not exposed. When we compare two years before treatment, 1962 and 1963, with the one when the Sullivan show hit the airwaves (1964) we find a highly significant jump in the share of images classified as having “mop-top” hair – which we define as being at the 75th percentile of the overall probability distribution\(^6\). Relative to the sample mean, the jump in 1964 in treated areas is large, suggesting an increase in the relative probability of more than 50%. The result is robust to controlling for school fixed effects (col. 2) and socio-economic characteristics\(^7\) and state fixed effects (col. 4-5). When we control for non-CBS stations, and the comparison group becomes areas without TV (col. 3), we find a similar-sized jump and no effect on the placebo. Results are similar for a five-year window around 1963. As take-up of the Beatles hair-style increases in the country as a whole, the sample mean post-treatment increases. Nonetheless, we find a 2-2.5 pp increase in the likelihood of adoption across specifications, and the coefficient on the placebo variable (col. 8) is once more negative.

Figure 9 presents a heat plot of Beatles-style hairdos by state over time. While there is an occasional efflorescence of a similar style in some states in earlier years, it never becomes dominant or even an important minority “taste”. The discontinuity after 1964 is visible across states. Some places see a more rapid rise in Beatles-style hairstyle – California, for example, has relatively rapid take-up in the three years after the show screened. Other states like Delaware and South Dakota show limited adoption initially, but eventually converge to high or very high levels of Beatles-style hair.


\(^7\) Total population (in logs, census 1960), share of men (census 1960), share of people between 14 to 17 in schooling (census 1960), share of urban population (census 1950), unemployment rate (census 1950). All of them included at county level.
5. Conclusions

The Cambridge Dictionary defines ‘culture’ as “a. the way of life, especially the general customs and beliefs, of a particular group of people at a particular time, b. the attitudes, behaviour, opinions, etc. of a particular group of people within society...”. In recent years, interest in cultural economics has increased sharply (Akerlof and Kranton 2000). Empirical studies of culture have focused almost exclusively on attitudes and beliefs, articulated either in surveys and written text, or reflected in actions. Customs and beliefs, and the extent to which they are specific to a particular group, however, comprise a much wider range of activities. In particular, visual culture and self-representation through style and fashion choices are arguably important but largely neglected aspects of cultural economics.

In this paper, we make two contributions. First, we introduce a set of methods and tools that allow rigorous and precise analysis of images as a source for cultural change. To do so, we use sparse feature vectors capturing key attributes of style. We train algorithms to identify style features in images. The vector representation in turn facilitates the use of standard measures of similarity. These can be used to map into two key dimensions of culture, homogeneity (“conformity”) and persistence. We also show how methods from the measurement of innovation – previously applied to patenting – can be applied to examine influential style changes.

Second, we apply our new methods to a large dataset of US high school senior images. We trace the decline and fall of image conformity in senior portraits, showing that the cultural revolution of the Sixties and early Seventies not only led to a sharp decline of conformity within each local high school; it also destroyed the – previously high – level of persistence, when portraits of the parent’s generation were broadly similar to those of their children. Using the Kelly et al. (2021) method for identifying influential innovation, we show how some areas of the US contributed markedly more to important new trends than others, and demonstrate that periods of peak creativity and influence are relatively brief.

The combination of new methods and new data also allows us to identify “insertion points” of new cultural trends, leveraging the granularity and frequency of our image data. We analyze changes in men’s hairstyles in the US during the Sixties, following the Beatles’ hallmark appearance on the “Ed Sullivan” show. A highly distinctive hair style, the “mop top”, attracted almost as much attention as their music. While this style was rare and not growing as a proportion of senior portraits before 1964, it quickly gained popularity afterwards. In the year of the broadcast, the effect is largest in areas where CBS, the TV network that broadcast the Sullivan show, had affiliated stations – and the further from a CBS station an area was, the lower the likelihood of a jump in mop top hairstyles among men in 1963. This in turn lead to wider adoption in the (youth) population at large, even outside areas with CBS coverage – resulting in a spectacular upward trajectory of fringe-style hairstyles. Within 3 years of the broadcast, an additional 15% of American teenagers sported Beatles-style hair.
The German philosopher Georg Simmel (1957) famously defined fashion as “a form of imitation..., paradoxically, in changing it differentiates one time from another.” How such imitation can lead to fashions that define a period is challenging to document empirically. The spread of “Beatlemania” in the US after 1963 as reflected in their hair style allows us to demonstrate where innovations come from, and how imitation drives changes in style. The pattern we document is compatible with interpretations emphasizing informational cascades behind rapid cultural, social, and political changes (Kuran 1989; Sunstein 2022).
References


Figures

Figure 1: Sample Images from High School Yearbooks

Note: First row is from 1964, second row is from 1984.
Note: This graph depicts the share over time for each discrete combination of style markers. Each image is assigned a style by collapsing the probability of each style marker. Styles that comprise less than 5% of the sample for all years are assigned Style 999 – Other. A description of styles follows:

Style 221: suit/short hair/normal tie/no glasses/no facial hair/no jewelry
Style 222: suit/short hair/normal tie/no glasses/yes facial hair/no jewelry
Style 223: suit/short hair/normal tie/yes glasses/no facial hair/no jewelry
Style 224: suit/short hair/normal tie/yes glasses/yes facial hair/no jewelry
Style 225: suit/short hair/bow tie/no glasses/no facial hair/no jewelry
Style 226: suit/short hair/bow tie/no glasses/yes facial hair/no jewelry
Style 233: suit/long hair/normal tie/no glasses/no facial hair/no jewelry
Style 234: suit/long hair/normal tie/no glasses/yes facial hair/no jewelry
Style 241: shirt with collar/short hair/no tie/no glasses/no facial hair/no jewelry
Style 242: shirt with collar/short hair/no tie/no glasses/yes facial hair/no jewelry
Style 265: shirt without collar/short hair/no tie/no glasses/no facial hair/no jewelry
Style 266: shirt without collar/short hair/no tie/no glasses/yes facial hair/no jewelry
Style 999: Others
Figure 3: Individualism and Persistence in US High School Yearbook Images, 1950-2010.

Note: All individuals across US, each compared with all individuals from same high school from their own year (individualism) and 20 years before (persistence). Cosine similarity is inverted for individualism, both are Z-scored.

Figure 4: Drivers of Individualism in US High School Yearbook Images, 1950-2010.

Note: Dots represent coefficient estimates from a Lasso regression of individualism score on style characteristics. Each dot represents a single coefficient for a style, derived from bi-variate regressions. Values greater zero indicate a positive contribution to students’ individualism score.
Figure 5: Persistence over Time.

Note: Individuals, drawn against 100 random people who attended their high school up to twenty years before them. Similarity scores normalised and are censored below the median z-score.
Figure 6: Influential Innovation in Style over Time, Decomposed into Forward and Backward Similarity

Note: For 10% of the national sample, we calculate the forwards and backwards similarities using the five years ahead and behind of each year for each image. We z-score the results for these three values and collapse to year means.
Figure 7: Kelly et al. Measure of Innovation in California, 1960-1990

Panel A

Panel B

Panel C

Panel D

Panel E

Note: For 25% of the images in California, we calculate the innovation index using a five year window forwards and backwards. We calculate city averages of innovation for each year from 1960 to 1980. Panel A shows a heat map of innovation according to the Kelly et al. measure for the period as a whole; Panel B is for 1950, C for 1960, D for 1970, and E for 1980.
Figure 8: Beatles-style “Mop-Top” Hair in High School Senior Portraits

(A) Coefficient - Probability of men with Beatles Hairstyle vs Time

- No CBS
- Yes CBS

(B) Probability of men with Beatles Hairstyle vs Km from School to nearest CBS Station

- 1963
- 1964

(C) Year 1963 and 1964

Note: Panel A. Probability of Beatles-style “Mop-Top” Hair in High School Senior Portraits (Event study - Average probability over time CBS vs non-CBS, standard errors are clustered at school level and includes school FE); Panel B. Binscatter of probability of Beatles-style hair, by distance to nearest CBS station, 1963 vs 1964, in km; Panel C. Kernel density function, probability of Beatles-style hair, CBS vs non-CBS, 1963 and 1964. CBS = 1 if CBS Station within 60 km from school.
Figure 9: Probability of Beatles-style “Mop-Top” Hair in High School Senior Portraits, Heatmap by State

Overall probability of men with Beatles Hairstyle

Note: Average probability of Beatles Hairstyle by state and year
## Tables

### Table 1: Results Beatles Regression

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Each observation corresponds to an individual senior portrait. The dependent variable equals 1 if an individual's hairstyle was at the 75th percentile of the probability distribution of having a beatles-style fringe. Short term sample uses a one year window around the year of treatment (1962-1964). The long term sample uses a five years window (1958-1968). Post equals 1 starting in 1964. Control Pre Mean refers to the average of control group in the pre period (until 1963). Control Post Mean refers to the average of control group in the post period (after 1964). Standard errors in parenthesis and clustered at school level. Significance indicated at the *p < 0.1, **p < 0.05, ***p < 0.01*
Appendix

Appendix I: Database Construction

a. Download yearbook pages from classmates.com

The data from classmates.com is acquired in two phases. First, we access classmates' “find a yearbook” query. A branching structure creates three lists of the states, cities, and high schools for which we have yearbooks. With this list of yearbooks, we iterate state by state, downloading each yearbook page image directly from the classmates.com images repository. These images are publicly available and do not contain any identifying information concerning the individuals depicted. We store each yearbook with four identifying pieces of information: The state, city as listed, high school, and year.

b. Crop all portraits

The yearbook images are transformed into grayscale and the border around the image is whitened. We define the background area of the image as the area characterized by the brightest color point. We convert all background pixels that lie within a brightness threshold to white or black, to then draw rectangles around black areas. Our portrait recognition algorithm checks whether these rectangles satisfy threshold criteria such as whether their area covers 1-33% of a page or the height and width 10-50% of the page. We crop the drawn rectangles in a page if three criteria are met:

- the number of faces (recognized by the cv2 model) vs the number of images in a page is close;
- at least 50% images only portray one face, and the face covers more than 30% of the image;
- there are at least two images on the page.

The portrait recognition algorithm can still be improved in these critical cases:

- The background color is similar to the image color

- The portraits have a darker connecting border compared to the background of the page
There is text overlaid and connecting different portraits

c. Select senior portraits

First, we block out the pages in the yearbooks into series of images by identifying consecutive runs of 4 pages that share similar image color and size. Second, we use a number of identifiers to give each run a score of the likelihood of being a senior page. Yearbook appearances are highly heterogeneous, but we can use a few key generalizations about yearbook characteristics to identify seniors. We use optical character recognition and information about the size, shape and color of the images to evaluate the following:

- Pages with seniors will likely be identified with the word 'senior' and do not contain other role names such as 'faculty', 'teachers', or 'juniors', for example.
- Senior pictures are more likely to be in color.
- Senior pictures are often larger than the rest of those in a yearbook.
- Pages with seniors on them will often say 'Class of [year]' where [year] matches the year of the yearbook listed on classmates.

With the crop and select pipeline, we estimate that we are able to select up to 70% of all senior portraits. The number of false positives is within 5%.

d. Building the classifiers

Images are manually labeled to create a training set. For each style marker we want to analyze, we label around 5,000 images. We encode each image with the following markers:

- Gender: female/male
- Hair: long/short
- Tie: no tie/normal tie/bow tie
- Clothing: dress/suit/shirt without collar/shirt with collar
- Glasses: yes/no
- Jewelry: yes/no
• Facial hair: yes/no

For each image, the classifier returns the probability of each tag occurring for every option above – each image has a probability p of “glasses” and a probability 1-p “no glasses”. Up to this point we have a collection of individual portraits, along with information on the year and the high school it belongs to. Next step is to convert each image into information that can be analyzed. In order to achieve this we train a classifier for each style, using the manually labelled images as our training sample. We pre-process the images before applying any machine learning algorithm, transforming the images from RGB to greyscale and resizing them. We train 7 classifiers (one for each style dimension), 5 of them performing a binary classification, and 2 (tie and clothing) a multi-class classification. The human-audited accuracies are estimated as follows:

• Gender: 93%
• Hair: 91%
• Tie: 97%
• Clothing: 76%
• Glasses: 99%
• Jewelry: 91%
• Facial hair: 70%

\[e. \text{ Geocoding the High Schools}\]

To geocode the high schools in the nationally representative sample, we use OpenStreetMaps API, and fill in missing information with manual searches. The California sample utilizes a slightly different geocoding approach than the national sample, utilizing the availability of high-quality data from the California State Government’s Geodata Portal. This dataset is advantageous in that it contains information on the locations of schools not currently open or those that have been merged with other high schools. We find that of the public schools in our sample successfully matched to the database, 85% are still active in 2022, 9% are closed, and 6% are merged. Those not matched to the database are geocoded by hand.

Appendix II: Details of Kelly et al. Analysis

We map the process of Kelly et. Al (2018) to our dataset by describing each image as a patent and its style markers as its textual content. Each cohort is described by an image id, year, and a vector of style markers. Kelly et. Al constructs their vector using "term frequency backwards inverse document frequency" (TFBIDF). Since our data arrives from the classifier as a fully formed table, we use the vector of styles as outputted by the classifier model as our vector for comparison, eliminating the need for computationally intensive normalization procedures as used by Kell et. al.
Because the algorithm is extremely computationally intensive, we use two stages of sampling to make the problem feasible. First, we draw a small sample of comparisons -0.5% of the data- for the calculations of forward and backward similarity. This is done across the entire range of the dataset, ensuring buffers on either end of the study period. For each run of the algorithm, we use the same comparison sample across all partitions of the data. Second, we sample from within our year range on which the innovation algorithm is computed. We draw from 10% of our nationally representative sample and 25% of our California sample. As in Kelly et. Al, we set a threshold - in our case .25 - to be classified as a binary to create a sparser matrix. The California analysis evaluates a quarter of the available data and uses 0.5% of the data as a comparison sample. This corresponds to approximately 930,000 images analyzed against 18,500 images each. This equates to approximately 1.7 billion pairwise similarities. The data is then collapsed to school-year cohorts, taking the average of the innovation scores in the school. We select a window of 5 years, as this is a reasonable window to expect fashion innovations to catch on. As Figure A.5 shows, trends generally hold across comparison windows, though larger windows produce more muted peaks and troughs.

**Appendix III: Details of Beatles Analysis**

First we run a classifier to measure the probability of a man with the Beatles hairstyle. For that we trained a Random Forest algorithm with 4,061 images and validated it over 947 images. The accuracy of the model is 83%. We classified all men in the national sample between 1955-1975 (1,449,490 obs).

To construct the variable of CBS/No CBS coverage we use the Broadcast Yearbook of 1964. We consider each TV Station that had CBS net affiliation. Then, we geocode each tower using the Homeland Infrastructure Foundation-Level Database from the US Department of Homeland Security. For those stations we don’t have information about the exact position, we input the latitude and longitude of the county’s centroid as an approximation. After that, we calculate the distance from each high school to the nearest station.
Appendix IV: Figures

Figure A.1: Example of Yearbook Images: Tift High School, Tift, Georgia, 1959

Figure A.2: Descriptive graphs – US Sample

(a) People  
(b) High Schools  
(c) Ratio Male  
(d) Mean cohort size

Note: Panel A. Number of students by year; Panel B. High Schools by year; Panel C. Share of males by year; Panel C. Mean cohort size by year.
Figure A.3: Share of US Sample Images Relative to Population Aged 15-19

Share sample over people 15 to 19 years old

Note: Population by Age and State level from NHGIS Census Records.
Figure A.4: Drivers of Persistence in US High School Yearbook Images, 1950-2010.

Note: Dots represent coefficient estimates from a Lasso regression of persistence score on style characteristics. Each dot represents a single coefficient for a style, derived from bi-variate regressions. Values greater zero indicate a positive contribution to students’ persistence score.

Figure A.5: Kelly et al. Measures at Different Time Horizons

Note: We calculate our innovation metric using forwards and backwards similarities of different sizes on 1% of our nationally representative sample (83,000 images). The results are z-scored and collapsed to year means.
Figure A.6: Kelly et al. Measure of Innovation by California City, 1950-1980

Note: For 25% of the images in California, we calculate the innovation index using a five year window forwards and backwards. We calculate city averages of innovation for each year from 1950 to 1990.

Figure A.7: The Beatles, 1964

(A)

(B)
Note: Panel A. On the Sullivan show, 1964; Panel B. Individual images
Figure A.8: Hair Style Classifier – Probability of Images being “Beatles-style” Mop-Top

Figure A.9: Google Ngram for “Cultural Economics”
Appendix V: Tables

Table A.1: Summary Statistics US Sample

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<td>Within high-school cos simil at t-1 years</td>
<td>7,055,443</td>
<td>0.727</td>
<td>0.110</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-2 years</td>
<td>7,616,503</td>
<td>0.737</td>
<td>0.141</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-3 years</td>
<td>7,028,798</td>
<td>0.746</td>
<td>0.143</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-4 years</td>
<td>6,939,912</td>
<td>0.741</td>
<td>0.145</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-5 years</td>
<td>6,872,336</td>
<td>0.737</td>
<td>0.146</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-6 years</td>
<td>6,794,470</td>
<td>0.732</td>
<td>0.148</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-7 years</td>
<td>6,724,771</td>
<td>0.728</td>
<td>0.150</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-8 years</td>
<td>6,646,108</td>
<td>0.724</td>
<td>0.151</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-9 years</td>
<td>6,575,551</td>
<td>0.720</td>
<td>0.152</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-10 years</td>
<td>6,470,332</td>
<td>0.717</td>
<td>0.153</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-11 years</td>
<td>6,384,757</td>
<td>0.714</td>
<td>0.154</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-12 years</td>
<td>6,293,761</td>
<td>0.711</td>
<td>0.155</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-13 years</td>
<td>6,207,637</td>
<td>0.708</td>
<td>0.155</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-14 years</td>
<td>6,128,178</td>
<td>0.706</td>
<td>0.156</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-15 years</td>
<td>6,050,348</td>
<td>0.704</td>
<td>0.157</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-16 years</td>
<td>5,955,388</td>
<td>0.702</td>
<td>0.157</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-17 years</td>
<td>5,856,351</td>
<td>0.700</td>
<td>0.157</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-18 years</td>
<td>5,756,390</td>
<td>0.698</td>
<td>0.158</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-19 years</td>
<td>5,635,429</td>
<td>0.697</td>
<td>0.158</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Within high-school cos simil at t-20 years</td>
<td>5,544,238</td>
<td>0.695</td>
<td>0.158</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Note: As we don’t have a balanced panel for every schools, there are some missing observations when calculating the cosine similarity between t and t-k.
### Table A.2: Summary Statistics California Sample

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>California Data (25% of all available portraits in the state)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Innovation - Forward Sim/Backward Sim -</td>
<td>918,685</td>
<td>1.000</td>
<td>0.646</td>
<td>0.545</td>
<td>1.545</td>
</tr>
<tr>
<td>Forward Similarity</td>
<td>918,685</td>
<td>0.824</td>
<td>0.107</td>
<td>0.112</td>
<td>0.956</td>
</tr>
<tr>
<td>Backward Similarity</td>
<td>918,685</td>
<td>0.824</td>
<td>0.106</td>
<td>0.106</td>
<td>0.963</td>
</tr>
<tr>
<td>Standardized values of Innovation</td>
<td>918,685</td>
<td>0.000</td>
<td>1.000</td>
<td>-9.900</td>
<td>11.865</td>
</tr>
<tr>
<td>Standardized values of Forward Similarity</td>
<td>918,685</td>
<td>-0.000</td>
<td>1.000</td>
<td>-6.672</td>
<td>1.237</td>
</tr>
<tr>
<td>Standardized values of Backward Similarity</td>
<td>918,685</td>
<td>-0.000</td>
<td>1.000</td>
<td>-6.801</td>
<td>1.313</td>
</tr>
<tr>
<td>Predicted Probability of no tie</td>
<td>918,685</td>
<td>0.625</td>
<td>0.479</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of bow tie</td>
<td>918,685</td>
<td>0.095</td>
<td>0.289</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of tie</td>
<td>918,685</td>
<td>0.281</td>
<td>0.445</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of glasses</td>
<td>918,685</td>
<td>0.061</td>
<td>0.239</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of no glasses</td>
<td>918,685</td>
<td>0.939</td>
<td>0.239</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of facial hair</td>
<td>918,685</td>
<td>0.308</td>
<td>0.429</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of no facial hair</td>
<td>918,685</td>
<td>0.692</td>
<td>0.429</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of dress</td>
<td>918,685</td>
<td>0.269</td>
<td>0.419</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of shirt with collar</td>
<td>918,685</td>
<td>0.208</td>
<td>0.385</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of shirt without collar</td>
<td>918,685</td>
<td>0.164</td>
<td>0.346</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of suit</td>
<td>918,685</td>
<td>0.359</td>
<td>0.473</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of long hair</td>
<td>918,685</td>
<td>0.429</td>
<td>0.488</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of short hair</td>
<td>918,685</td>
<td>0.571</td>
<td>0.488</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of jewelry</td>
<td>918,685</td>
<td>0.265</td>
<td>0.437</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Predicted Probability of no jewelry</td>
<td>918,685</td>
<td>0.735</td>
<td>0.437</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

### Table A.3: Summary Statistics Beatles Sample

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Beatles Sample: all men in US sample between 1955-1975</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted Probability of Beatles Hairstyle</td>
<td>1,444,383</td>
<td>0.350</td>
<td>0.247</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Dummy - Percentile(Prob(Beatles)) &gt; 75th</td>
<td>1,444,383</td>
<td>0.244</td>
<td>0.249</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Km to closest CBS Station</td>
<td>1,444,383</td>
<td>58.474</td>
<td>49.267</td>
<td>0.643</td>
<td>289.305</td>
</tr>
<tr>
<td>Km to closest non CBS Station</td>
<td>1,444,383</td>
<td>48.577</td>
<td>49.293</td>
<td>0.508</td>
<td>358.689</td>
</tr>
<tr>
<td>Dummy - Distance to CBS Station &lt; 60km</td>
<td>1,444,383</td>
<td>0.620</td>
<td>0.485</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Dummy - Distance to non CBS Station &lt; 60km</td>
<td>1,444,383</td>
<td>0.704</td>
<td>0.457</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Table A.4: Demographic Statistics by county and CBS/No CBS
<table>
<thead>
<tr>
<th></th>
<th>No CBS</th>
<th>Yes CBS</th>
<th>Difference (No - Yes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total population, 1960</td>
<td>62807.705</td>
<td>172100.547</td>
<td>-109292.842**</td>
</tr>
<tr>
<td>Share of men, 1960</td>
<td>0.500</td>
<td>0.494</td>
<td>0.006**</td>
</tr>
<tr>
<td>Share non white people, 1960</td>
<td>0.092</td>
<td>0.089</td>
<td>0.004</td>
</tr>
<tr>
<td>Share of population (14 to 17) in schooling, 1960</td>
<td>0.869</td>
<td>0.877</td>
<td>-0.007</td>
</tr>
<tr>
<td>Share urban population, 1950</td>
<td>0.354</td>
<td>0.520</td>
<td>-0.166**</td>
</tr>
<tr>
<td>Unemployment Rate, 1950</td>
<td>0.042</td>
<td>0.041</td>
<td>0.001</td>
</tr>
<tr>
<td>Observations</td>
<td>319</td>
<td>318</td>
<td></td>
</tr>
</tbody>
</table>

Descriptives are done at the county level. This table reports means and differences in demographic variables between CBS and No CBS group. We use Demographic Variables from Census 1950 and 1960 available at NHGIS. As the variable CBS/No CBS is constructed at high school level, there are some counties that have school with CBS signal and schools without CBS signal. Only counties without any school with CBS signal are considered as No CBS counties.