LIS
Working Paper Series

No. 755

Creators' Income Situation in the Digital Age

Alexander Cuntz

December 2018

This working paper has been published as:
Economic Research Working Papers, no. 49 (December 2018),
World Intellectual Property Organization, Geneva

Luxembourg Income Study (LIS), asbl

Creators' Income Situation in the Digital Age

Alexander Cuntz

ABSTRACT

The digital transformation imposes both opportunities and risks for creativity and for creative employment, with implications for trends in income levels and the distribution of income. First, we consider skill-biased technological change as a determinant of income and labor market outcomes in the arts. Arguably, the IT revolution has changed the demand for certain skills, with creative occupations being more in demand than general employment. Second, we consider declines in the costs of generating new works and artistic experimentation due to digital technologies, and their effect on the barriers to entry in labor markets. Third, we touch upon the rise of online contract labor in certain creative professions as a determinant of income. Here, online platforms can change creators' access to work opportunities and it may alter the way income is distributed.

We find that wage trends for creative workers in the digital age outperform general trends in the population: based on various data sources and various ways to identify creators, we see creators losing less or even gaining a better income position in relative terms. From a policy perspective, results do not lend support to the idea that creators' income situation has systematically worsened with the rise of the internet and its intermediaries. Evidence on changing distributions of income is ambiguous as trends differ from one country to the next.

KEY WORDS: creative economy, artist, creativity, occupation, labor market, self-employment, income, wages, distribution, skill biased technological change, digital technology, internet

JEL CLASSIFICATION: J24, J28, J31, L82, O15, O33, O34, Z10

DISCLAIMER

ACKNOWLEDGEMENT

The author is thankful and indebted to the inputs, support and kind review of the following people: Francesco Bogliacino, Evelyn Brislinger, Carsten Fink, Christian Handke, Anaïs Humbert, Andreas Kißling, Angela Miller and Ivet Solanes Ros. I am also thankful to participants of a WIPO internal seminar discussing the preliminary results of this report. Moreover, I would like to express my gratitude for data sharing and data support by the following institutions and initiatives: The European Values Study and the GESIS team,[*] the Integrated Public Use Microdata Series (IPUMS-USA) database,[†] the German social insurance scheme 'Kuenstlersozialkasse' (KSK),[‡] the Luxembourg Income Study (LIS) database,[§] and the Strategic National Arts Alumni Project (SNAAP).[**]

[*] EVS (2015): European Values Study Longitudinal Data File 1981-2008 (EVS 1981-2008) – Restricted Use File. GESIS Data Archive, Cologne. ZA5174 Data file Version 1.0.0, doi:10.4232/1.5174

[†] Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D010.V8.0

[‡] http://www.kuenstlersozialkasse.de/service/ksk-in-zahlen.html, last accessed on July 30, 2018.

[§] Luxembourg Income Study (LIS) Database, http://www.lisdatacenter.org (multiple countries; June 2017 to June 2018). Luxembourg: LIS.

[**] http://snaap.indiana.edu/, last accessed on July 30, 2018.

CONTENTS

INTRODUCTION

Nick Cave [singer], why are you creative? Because I have to be.
Yoko Ono [visual artist], why are you creative? Because I am what I am.
Willem Dafoe [actor], why are you creative? I like how I feel how I think when I am making things.

Cited from Hermann Vaske,
2018 Exhibition in the Museum of Communication, Berlin, and
the film 'Why Are We Creative? The Centipede's Dilemma'.

The creative economy is a frontrunner and testbed for online experimentation, including in its labor markets. Nowadays, many creative jobs are exclusively transacted online and over long distances, they are widely spread across industrial activities, and they are not limited to core copyright-based industries. Jobs often go along with flexible and risk-prone arrangements for creators, such as high rates of self-employment and freelancing, and multiple job holdings. In addition, in the more recent 'value-gap' debate on stakeholders' revenue sharing, some commentators have argued that creators have become worse off over time and have been unfairly treated since the rise of online environments. However, in general, it seems that these job prospects have not stopped artistic talent from entering labor markets. The state of creators' income situation in the digital age is ultimately an empirical question. This study seeks to shed light on this question by exploring a number of 'hard' data sources on the evolution and distribution of creators' income.[1]

Waldfogel and colleagues have prominently proclaimed a 'golden age' of content for consumers in the digital age, with increasing numbers of works being released in many sectors of the creative economy (Waldfogel 2017a). Changing supply is welfare-enhancing and mainly due to substantial cost decreases in the production, distribution and promotion of creative works, with independent production and self-publishing accounting for some of these new works (Waldfogel 2012; Aguiar and Waldfogel 2016; Waldfogel and Reimers 2015; Handke et al 2015) . In addition, the increase in the supply of works in sectors such as music, movies, books or television does not seem to come at the expense of quality of works. Indicators of quality, such as consumers' usage and ratings of works, evidence stable or even increasing quality of supply (Waldfogel 2016, 2017b). At the same time, arguably, a growing cadre of online reviewers of new works extends the means of product discovery for consumers, lowering their search costs in the face of rising supplies of these experience goods, even though this may differ from one sector to another (Hviid et al 2017a).

However, this line of research does not explain what the quantitative growth in supplies across sectors means for original creators, and whether or not their income situation is changing, in particular in bottom and medium tiers of the income distribution. So, for example, an increase in content may be traced back in value chains of the creative economy to an increase in incumbents' artistic productivity, or the content upsurge may well be rooted in an increasing number of creators entering these markets. These two scenarios have different implications for labor market outcomes, the 'financial health' of creators and the sustainability of their careers, and they are more or less effective in supporting other goals of copyright policy.[2]

Reflecting the opportunities and risks for creativity and for creative employment in the digital age, our study proceeds as follows:

- First, we consider skill-biased technological change as a determinant of income and labor market outcomes in the arts. Arguably, the IT revolution has changed the demand for certain skills, with creative occupations being more in demand than general employment.

- Second, similar to the argument of Waldfogel and others, we consider declines in the costs of generating new works and artistic experimentation due to digital technologies. However, our research focuses on the implications for original creators, as cost declines might have lowered the barriers to creative labor markets.

- Third, we touch upon the rise of online contract labor in certain creative professions as a determinant of income. Here, online platforms can change creators' access to work opportunities and it may alter the way income is distributed.

The empirical study is based on the Luxembourg Income Study (LIS) database covering several countries around the world and national micro-level income data since the turn of the century. In addition, we build the quantitative analysis on various other data sources such as large-scale surveys among alumni from U.S. music and art schools, and insurance and revenue records on self-employed artists working in Germany.

Admittedly, the study does not attempt to cover all relevant aspects of the digital transformation in these sectors, and stays silent on many aspects that may matter for stakeholders, but it does so in order to ensure that the research is manageable and concise.[3] Moreover, it takes a slightly broader stance on artists as original creators of copyrighted works – that is literary, musical and artistic works – by also including creative performers that add substantial value via reinterpretations of works. In what follows, we use either 'creators' or 'artists'.

LITERATURE REVIEW AND HYPOTHESIS

Artists' motivation and creativity

Why are you creative? In most cases, professional artists want to earn a living from being creative. However, pecuniary incentives and income generated from artistic endeavors only explains some of the overall commercially *and* non-commercially orientated creative activity we observe. Thus, it is instructive to first briefly survey what the economic literature identifies as the main motivators of creators.

Creators tend to accept below average pecuniary rewards for their creative activities. This distinguishes their activities from many other types of tasks that respond to monetary incentives alone and thus conform to standard economic theory (Arrow 1972). This seems to apply in online contexts where quality of creative output does not necessarily rise with greater pecuniary reward (Huang et al 2013). Part of the reason is that creators more than other workers tend to be driven by intrinsic motivators, such as curiosity, the joy of play, or self-determination/manifestation. Simply put, intrinsic motivation relates to activities one undertakes because one likes to do them or derives some satisfaction from them. In this context, working autonomy and meaningful and challenging tasks (rather than routine and zero-context ones) in offline and online environments are important preconditions for intrinsic motivation, which, in turn, is required for creativity to flourish fully (Amabile 1998; Chandler and Kapelner 2013). However, setting some constraints may not necessarily have adverse effects on creativity (Baer and Oldham 2006).

Similarly, altruistic behaviors and social preferences likely help explain some of the other intrinsically motivated creative activity we observe (Fehr and Schmidt 2006). Surprisingly, this type of behavior has received little to no attention in the cultural economics literature so far. Examples of altruistic behavior – explicitly taking into account the outcome of one's own decision on others' payoff – include donating or repaying a favor. These behaviors deviate from the standard *homo economicus* concept and are often associated with fairness and reciprocity notions in modern economics, even though not exclusively. Notably, this coincides with some of the arguments made on social norms in many creative and cultural activities. Gift-giving and volunteering by artists, as well as donations – 'serving' rather than pay – to artists seem to be dominant social norms, while a commercial orientation and market transactions still seem less well-accepted *modus operandi*, and the latter are sometimes 'covered up' (Abbing 2004).

Moreover, extrinsic motivators such as peer recognition and other types of non-pecuniary and 'social' incentives matter and tend to be more conducive to creativity than to many other tasks. For example, it seems likely that an artist, similar to a scientist, prefers being granted a prize by his or her peers over a lump-sum money transfer of the same amount, because he or she derives reputational rewards from the former (Neckermann et al 2014; Bourdieu 1992). In these cases, a mechanism that allows for the attribution of works to specific creators is an important precondition.

Any well-informed incentive scheme design targeting greater creativity and creative occupations (including the incentives provided via copyright laws) should account for the trade-offs that govern intrinsic and extrinsic motivators. When provisioning creators with extrinsic incentives that are perceived as controlling rather than supportive, artists' intrinsic motivation may be "crowded-out", as stipulated in the cultural economics and earlier on evidenced in the cognitive psychology literature (Frey and Jenen 2001; Bénabou and Tirole 2003). Other specific trade-offs or complementarities between different types of non-monetary incentives, such as altruism and peer recognition, to our best knowledge, have not been studied extensively.

In addition, creators seem to ‘immerse’ themselves in the very process of creation and derive extra utility from doing so. On one hand, they attach greater value to their own creative work than others would be willing to pay. This gives rise to a so-called ‘creativity bias’ in valuation – an over-optimism as regards the quality of their own work – as more recent experimental evidence suggests (Buccafusco and Sprigman 2011). On the other hand, the extra utility derived from creative tasks may also partially explain why artistic occupations are typically associated with significantly higher levels of job satisfaction compared to most others (Bille et al 2013; Steiner and Schneider 2013).

The main takeaway from these strands of the economic and psychological literature is that artists may have different criteria for and conceptualizations of what constitutes a ‘good’ job and income, as they may derive value and satisfaction from their work in a variety of ways aside from income and commercial success (sometimes referred to as ‘psychic income’). This insight helps us to better understand some of the stylized facts on artistic labor markets, as well as the choices and changes observed in creative activity and employment in the digital age.

Stylized facts on artistic labor markets (supply)

Economists have developed labor market models specific to the arts that account for some of the divergence in the motivation sets of creators. For example, the 'work-preference' model builds on assumed violation of the commonly observed trade-offs between disutility of work and the utility derived from leisure and income (Throsby 1994). Meanwhile, various extensions of the basic model have been proposed, considering a dynamic set up or a preference of artists for leisure time (Popović and Ratković 2017; Casacuberta and Gandelman 2011; Caserta and Cuccia 2001). Simply put, Throsby's basic model states that artists prefer to spend more hours working in the arts over receiving higher pay and more leisure time in any other type of work. Accordingly, the model predicts that artists tend to work longer hours in relatively low-paid arts jobs and will attempt to cross-subsidize from work outside the arts until their minimum subsistence is covered, thereby maximizing the time worked within the arts and compensating for foregone income. Such cross-subsidizing also may take place via family endowments and spousal earnings (Towse 1996), sharing income risks at the household level and compensating for income 'penalties' on the creator's side, or via collective action of artists pooling their resources and risks in groups (Simpson 1981; Crane 1987). Of course, public sources of income such as subsidies, grants or sponsorship are also important in many artistic disciplines (Baumol and Bowen 1966).

Throsby and various other scholars (Cowen and Tabarrok 2000; Popović and Ratković 2017) have noted that, due to the specific trade-offs described above, there is a continuous oversupply of artistic labor (i.e. hours worked in the arts), job rationing and excess entry of artists into these markets. This means that wages cannot serve as well-functioning prize signals, balancing demand and supply in markets (Menger 1999). In turn, this can lead to fierce artist competition and anomalies in labor markets, such as employment and unemployment increasing simultaneously (while standard theory in this case would predict a decrease of unemployment with rising number of successful hires). The work preference model's implications have been empirically tested and largely confirmed, with very few exceptions. The broad evidence lends support to a general preference and earnings penalty for arts work, i.e. higher income outside the arts does not induce mobility/transitioning of artists, and cross-subsidizing arts work by working outside the arts (Alper and Wassall 2006; Throsby 1994; Robinson and Montgomery 2000). However, higher wages in arts occupations do not necessarily increase (decrease) the supply of hours worked in the arts (outside the arts), but, notably, the data used often does not account for sources of non-labor income and variation in labor demand (Rengers and Madden 2000). Moreover, certain studies suggested that, rather than investigating 'psychic income' via artists' labor supply choices, their utility from work should be *directly* measured, for example, via their job satisfaction scores (Steiner and Schneider 2013).

As Menger explains, creators often find themselves in a somewhat paradoxical situation because 'as an occupational group [they] are, on average, younger than the general workforce, are better educated, tend to be more concentrated in a few metropolitan areas, [however, they] show higher rates of self-employment, higher rates of unemployment and of several forms of constrained underemployment, i.e., non-voluntary part-time work, intermittent work, fewer hours of work, and are more often multiple job holders' (Throsby and Thompson 1994; O'Brien and Feist 1995 as cited in Menger 1999). Furthermore, it seems hard to classify high self-employment rates in the arts as either being based on an entrepreneurial 'necessity' or 'opportunity' alone (Block et al 2015): High unemployment rates in many of these sectors clearly corroborate the former rationale. However, greater risk tolerance, occupational autonomy and a strong sense of self-achievement are important motivators for creators, lending support to the latter rationale. Moreover, similar to the income penalties in artistic labor markets, entrepreneurs in general sacrifice earnings to be entrepreneurs, indicating that non-pecuniary motivations must also be present (Kerr et al 2017).

Notably, relevance and uses of creative and cultural skills have expanded, with occupations now spreading across a number of industrial activities. Therefore, these occupations are not *per se* limited to what has been originally framed as ‘creative industries’, as evidenced in recent studies focusing on the United States of America, Canada and creative labor markets in the European Union (Nathan et al 2015; Nathan et al 2016). However, it is difficult to tell whether the expansion to outside industries was merely reflecting demand- *or* supply-driven trends. On one hand, a growing demand for innovation in ‘non-creative’ industries could have nurtured labor demand for creative talent and artistic occupations. Similarly, Baumol and Bowen (1966) argued for a cost disease in the arts and in other labor-intensive services, with these services attracting more workers while decreasing in labor productivity relative to most other sectors. On the other hand, diversification of income risks via multiple job holdings and the inter-sectoral mobility of creators may also account for some of the occupational patterns observed. Like property owners spread their risk by putting bits of their property into a large number of concerns, artists who hold multiple jobs put bits of their efforts into different concerns (Dreze 1987). Furthermore, on an individual-level, ‘hybrid’ job profiles tend to combine different roles and help occupational risk diversification, blurring boundaries between management and pure art work. For example, Moulin (1992) and Hesmondhalgh (1996) discuss entrepreneurial artists who work as both performers and producers of services in the visual arts and in dance music, respectively.

There are other important rationales as to why we see a large amount of informal and flexible work arrangements in creative and cultural occupations. These are not based on distinct sets of motivators and work preferences of creators alone, as stipulated in Throsby’s work. Caves (2000) and several other authors point to a high ‘built-in uncertainty’ that not only matters for individual-level, occupational choices over the course of an artistic career and extensive on-the-job training, but for the way *specific* markets are organized around offering experience goods of *ex ante* unknown value and the way its *organizations* take on risks via greater organizational flexibility. These risks are commonly associated with very ‘high rates of change over time of the content of activities’ (Stinchcombe 1968) and fast-moving, unpredictable consumer tastes subject to informational cascades (Bikhchandani et al 1992). As Atladóttir puts it, in markets where experience goods are on sale, ‘unless organizations and artists can have [keep] certain control over their works, they would not be able to benefit from later success that might come about and that would make works valuable that at the time they were produced had a low value’ (Atladóttir et al 2014). Radical uncertainty in cultural and creative industries closely relates to what Knight (1921) has considered uncertainty. When the probability of future states of the world is knowable, or at least to a certain degree, risks can be priced and diversified away, while in the case of Knightian ‘uncertainty’ it is hard to even describe exactly or quantify what the future states might be (Kerr et al 2017).

This is also reflected in most organizations’ preference for flexible, short-term and performance-based contracting of creators, which not only applies to temporary or smaller organizations but to the practices of many larger organizations in these sectors. Such work arrangements minimize employer’s overhead costs and better suit their diverse and project-orientated requirements, particularly for larger artistic endeavors. For example, in film, opera or theater performances, ‘a large number of different artistic occupations and crafts’ are combined in projects and these ‘new teams are [quickly] formed and then dispersed’ once the production is over (Menger 1999). However, such ad hoc arrangements do not preclude industry-wide arrangements as regards wage standards and fringe benefit schemes. Certain sectors of the creative economy exhibit strong or even expanding trade unionization in some countries (Paul and Kleingartner 1994). For example, this has been the case for the group of ‘free’ performers in the United States and United Kingdom, i.e. performers not regularly employed in state-owned and managed sites (Towse 2014).

Under radical uncertainty, talent selection and occupational learning in casual work arrangements often happen on a hiring-calls-for-more-hiring basis, i.e. a candidate's previous hiring record heavily conditions success in future job search and hiring. The latter creates a self-reinforcing, reputational mechanism that bears risks of a talent 'lock-in' for producing companies, and it may also deter new artistic talent from entering markets and deprive them from valuable learning opportunities. That said, educational attainment at earlier career stages does not seem to serve as a meaningful screening device for creative talent. Income from primary creative practice is not, or is only very weakly, responsive to formal training in the arts (Filer 1990; Towse 1996; Throsby 1996), and those artists unaware of their low/er innate abilities will continue to invest in schooling.[4] It is only when creators receive (informal) on-the-job training and in the course of practice that their 'true' ability is revealed to themselves and to other parties in the market, resulting in an evolutionary and costly trial-and-error-type process (Miller 1984; Caserta and Cuccia 2001). These strong informational barriers/asymmetries and sorting mechanisms in the market make risk-tolerant or -loving creators more likely to enter artistic labor markets in the first place. At each point in time, these labor markets tend to face shortages of talented workers and an excess supply of less talented ones (Towse 1996).

It should also be noted that casual labor relationships may come with significant transaction costs for *ad hoc* contracting organizations when compared to a long-term assignment of workers. This, at least partially, explains why we also see spatial agglomeration in certain sectors and locations, such as movie production in Hollywood (Quingley 1998), where economies of scale make up for some of the downside effects of 'contractual disintegration' in the production process of culture and art. Moreover, there is a growing body of research – outside cultural economics – on the ambiguous and sometimes adverse effects of flexible employment structures on the productivity and innovation at firm and industry level (Cetrulo et al 2018). Here, the standard economic argument is that labor flexibility, such as temporary contracts, are ensuring a better match between the demand for and supply of skills and a faster, lower adjustment-cost response to high consumer demand volatility (OECD 1994). However, this view likely underappreciates the role of accumulation of tacit knowledge and organizational competences where labor flexibility may weaken creative and innovative output (Cetrulo et al 2018).

Empirical evidence on artist income

As the binary stereotype goes, artists are permanently starving and impoverished, or they end up extremely rich and famous. The correlation between efforts and earnings seems weak for many professional artists (Moulin 1992). At the same time, young people often opt for an artistic career because of the 'high esteem' and prestige of the arts in society (Abbing 2004). However, the actual success and earnings flows of artists are harder to predict than for most other types of occupations, due to radical uncertainty in these markets and how artists cope with this uncertainty throughout their career. The economic literature on artistic earnings has mainly focused on three aspects: an assessment of creators' income levels, the distribution of income and, to a much lesser degree, income trends over time.

First, most previous research on income levels suggests that creative workers earn less than other workers, using either total population income averages or a reference occupational category with comparable human capital characteristics such as education, training or age (among many others, Towse 1993; Elstad 1997). The income penalty in many of these older studies ranges between 7 to 15 percent (Frey and Pommerehne 1989). The stylized fact of a low-income profession seems to hold over various countries and many artistic disciplines (Rengers and Madden 2000). However, there are notable exceptions. For example, Filer (1986) refuted the 'myth of the starving artist', based on U.S. census data. He estimates that artistic occupations generate comparable income and artists would have a higher probability of remaining in their occupation over time than workers in non-artistic occupations. Their jobs are more stable.

Moreover, research outcomes also differ substantially for specific artistic disciplines and by type of work arrangement. Research on visual artists by Kretschmer et al (2011) suggests that the median earnings of designers of creative works and the household level income of photographers are both higher than U.K. national averages. Research on established musicians in Uruguay by Casacuberta and Gandelman (2011) considers a sample of surveyed artists as 'middle class' as regards their income levels. In the case of performers, those working under more flexible arrangements often earn higher *hourly* wages than those employed on a long-term basis, i.e. they receive a 'wage premium' in the performing arts (Menger 1999). By the latter premium, employers seem to compensate for uncertain labor prospects and secure the availability of underemployed creators on these labor markets. However, hourly wages for greatly underemployed workers are not higher than for their more successful colleagues and, thus, they do not fully make up for the lower total number of hours worked. Extending this perspective, when self-employed artists are compared to those salaried by a cultural organization, the former obtain higher levels of non-monetary satisfaction or compensating psychic income, even though they generate lower average income (Taylor 1987).

Most of the mixed research results on income levels can be traced backed to varying approaches researchers have used (Throsby 1990). Studies have deployed various data sources, definitions of income periods and of artistic occupations, control group approaches, the way average income levels are measured and the level on which income is aggregated. Income levels may be aggregated on an hourly, weekly, monthly, annual or even lifetime basis, and can also be disaggregated into art, art-related and non-art sources, rather than studying total income on individual or on household levels alone. Also, as many artists are self-employed, one cannot easily equate fewer working hours with unemployment spells. As discussed above, artistic income depends heavily on whether works are in demand once created, i.e. whether works can be (immediately) sold and at what price. In addition, it does not necessarily derive from a quantity of working time dedicated to the arts at a given wage rate (Frey and Pommerehne 1989). It seems differences in annual income levels could reflect differences in hours worked more than differences in wage rates (Debeauvais et al 1997).

Second, previous research on the distribution of artists' income argues that many artists face larger income inequality and variability (Menger 1999). Again, this parallels research outcomes from the entrepreneurship literature as many artists across disciplines are self-employed. Here, a greater income dispersion is observed among entrepreneurs (across sectors) when compared to a reference group of regularly employed individuals (Halvarsson et al 2018). Entrepreneurship is a source of enhanced income mobility for some but results in lower than-average incomes for the large fraction of self-employed (Åstebro et al 2011). Moreover, disaggregated earnings from specific, non-earnings income sources such as copyright royalties tend to follow a similar skewed distribution pattern (Kretschmer et al 2010). However, these earnings typically contribute only a small fraction to artistic income and are thus less important as a source of total income (Atladóttir et al 2014).

In Rosen's (1981) 'superstar' model and in extensions (Adler 2006), a winner-takes-all tendency in creative labor markets is one of the reasons why we see a highly skewed distribution of income. The model suggests that small differences in artistic talent can become magnified in wide earnings differences in these particular markets, with very few top earners sharing most of the returns and a majority of earners below national average (Caves 2000; Towse 2010). That said, the initial distribution of talent or quality of the work alone cannot explain the variation in income returns. Rather, it is consumer behavior, such as fads and fashions – i.e. 'bandwagoning' on peer's consumption choices – as well as technologies that allow superstars to reach a large audience at almost zero reproduction costs, that play a pivotal role for skewedness of income distributions (Handke et al 2016). A different stance in terms of model logic is taken by Tervio (2009): here, a highly skewed distribution of income is the equilibrium outcome of underinvestment in talent discovery and experimentation, i.e. costly discovery requiring use of talent of ex ante unknown quality.

A different but related argument is made by evolutionary economics. It views the emergence and success of a creative work as resulting not necessarily from predictable 'mutations' in the skills possessed by individual artists, and not – as standard economics would have it – as an optimal plan implemented by a globally maximizing agent (Caserta and Cuccia 2001). Again, the discovery process from an evolutionary perspective is considered more random in the very beginning, with artists being more short-sighted and less capable of planning. So, in principle, a superstar at early career stages could be an artist with no more talent than any other. However, after an initial talent selection by an expert, the market 'locks-in' to an artist, generating superior rents for those artists who come first in the market. For example, in the American action painting movement, the artists who succeeded first – such as Pollock, De Kooning or Rothko – maintained a difference in quotation compared to any other artists of the same school that entered later (Sacco 1998). In this way, evolutionary economics may also explain some of the income variation observed in artistic markets.

Third and more broadly, time trends in aggregate income levels and, more specifically, individual level income streams over the course of an artistic career have been less studied empirically. Some of these studies have looked at time trends using quasi panel or panel data approaches. For example, Alper and Wassall (2006) show that over a 60 year period, disparities in unemployment and annual hours worked shrink to a certain degree, even though the fraction of artists in the total working population increases. Their research is based on U.S. 1940–2000 census data and a smaller sample of career-level data from 1979–1998 longitudinal surveys. However, disparities in artists' earnings levels do not shrink in the same period. At the outset, earnings were lower than in the reference group, partly because artists tended to work fewer hours, and earnings were more concentrated. That said, U.S. earnings inequality measures for artists increase faster over the observation period than in the tested reference groups. For a small panel of Dutch visual art graduates, Rengers (2002) found that inequality in hours worked, wages and earnings diminished over the time 1980–1996, consistent with the human capital model. Moreover, he estimates that art school graduates who left the arts for non-artistic occupations are not penalized in terms of earnings. For Australian artists, Throsby and Hollister (2003) show that earnings from their art work decreased throughout 1983–2002 and fewer artists held multiple jobs. However, while real *total* earnings decreased from 1983–1993, it rose back to similar levels in 1993–2002. At the same time, artists spent considerably more time working in the arts in 1993 (as compared to 1983), but then reduced dedicated time in 2002 (as compared to 1993).

Career progression is another important factor in the observed levels and dispersion of income. Differential drop-out rates and lower number of hours worked may explain why income gaps between younger and older artists are typically wider than for other workers (Throsby 1999; Rengers 2002). In a similar vein, sources of income and multiple job earnings are much more dispersed at the beginning of an artistic career and come under greater control with increasing reputation (Menger 1999). Once the market prizes and recognizes them as artists, and artists become more aware of their talent, they may also it find easier to predict success of their work. However, due to the on-the-job training opportunities they seek and the returns from psychic income, early-stage artists in particular will accept below average monetary rewards. Also, Towse (2006) suggests that young artists in particular suffer from an overconfidence bias concerning their own creative skills, and therefore these cohorts are oversupplying labor more than others.

The digital transformation of artistic labor markets: hypothesis development

The transformation in the digital age is not limited to structural change in the creative industries and renewal of its incumbent organizations and institutions. It also changes the way artistic labor markets operate and, accordingly, outcomes on these markets. Due to changing cost structures for creators in the digital environment, it also affects the way new works are financed, collaborated on and generated.

However, it is unlikely that these changes and their implications for income and productivity will apply across all artistic disciplines universally. So far, adoption of digital technologies is most widespread in music, film, books, photography and design occupations, or entire sectors such as gaming can be considered 'born digital'. By contrast, adoption seems much slower in the performing arts, and changes seem less strong on the side of creators where digital cost impact accrues further downstream in distribution and retailing, or when artistic works are non-reproducible or cannot be stored (Atladóttir et al 2014; Handke et al 2016; Stoneman 2015). In general, creators' perceptions of these changes are mixed, but artists who use digital technology are more optimistic about the outcome of these changes (Throsby and Zednik 2010; Poort et al 2013).

Several authors have modeled and empirically tested 'skill-biased technological change' in labor economics to explain reallocations of skills and tasks between labor, capital and trade over time, and importantly, associated changes in real wages and in polarization of income (Acemoglu 2002; Acemoglu and Autor 2011; Atkinson et al 2011). These models also (but not exclusively) apply in the context of the IT-based transformation of the economy. And, most of this research has focused on the United States (Brynjolfsson and McAfee 2014). This research is part of a wider discussion among economists that focuses on rising income inequalities globally (Facundo et al 2013; Piketty 2014; Piketty et al. 2018). Simply put, skill-biased technological change is a shift in the production technology that favors 'skilled' over 'unskilled' labor by increasing its relative productivity and labor demand. In this case, IT automation and offshoring of unskilled, routine tasks raise relative demand for workers who can perform skilled, non-routine tasks, complementary to new technologies. In extensions of Acemoglu's canonical model, it is argued that the wage premium from skill-biased technological change goes disproportionately to those at the top and at the bottom of the income and skill distribution, not to those situated in the middle (Autor 2015).

More specifically, non-routine tasks in these models are either abstract or manual ones that require problem-solving, intuition, persuasion and, notably, creativity (Autor et al 2003). Professional, managerial, technical and creative occupations – such as law, medicine, science, engineering, management or arts – rely upon these types of tasks and their workers commonly have high levels of education and analytical capability. Moreover, creative, analytical and problem-solving tasks are complementary to computer technology, because they typically draw heavily on information as an input. In this way, when the price of accessing, organizing, and manipulating information decreases as in the digital age, these tasks tend to be complements than substitutes. Alternatively, many routine tasks are characteristic of middle-skilled, cognitive and manual jobs such as administration, clerical work, repetitive production and monitoring ones. As these tasks follow precise, well-understood work procedures, they can be and are increasingly codified in computer software and performed by machines, or they are electronically offshored to foreign worksites (Bessen 2016).

How do these models of skill-biased technological change apply to creators and artists' in the digital ages? There is good reason to believe that creative skill sets, in general, complement rather than substitute new IT-based technologies, as efficient use of technologies requires such skills. Arguably, creators may have largely benefited from skill-biased technological change and income polarization, as demand for abstract, non-routine skills increases and so do wages for such tasks. Any type of creative occupation heavily relying on these skills – i.e. pure art work, art-related and even non-art (Throsby 1994), and whether having the purpose of generating artistic income or subsidizing artistic income – is likely to suffer less from downward competitive pressures on income due to IT-based automation and offshoring of routine tasks (Bakhshi et al 2015). In a similar vein, skill-biased technological change seems to favor precisely those occupations where learning and investment in entirely new skills – for example, use of innovative desktop publishing technology – relies on on-the-job training rather than on formal educational attainment (Bessen 2016). In many creative occupations within and outside the arts, on-the-job learning continues to play an important role in work arrangements, and income returns from formal education in the arts are typically low or even negative (Miller 1984; Towse 1996; Throsby 1996). Accordingly, it seems likely that creators and artists adapt more easily and faster to new digital skills in demand, also implying higher salaries, at least in those sectors of the creative economy that experienced early digital transformation. Income in digitally laggard sectors should also have resisted downward pressures on income simply because of the abstract and non-routine nature of the skills creators supply. Therefore, we hypothesize,

> **#1** As skill-biased technological change induces polarization of income in the total working population over time, workers in creative occupations earn a *wage premium* when compared to average income of the total working population (‘level effect’).

A recent strand of the labor market literature is less optimistic as regards the income resilience of skills used in abstract, non-routine tasks, as evidenced by research looking at emerging online contract labor markets (sometimes referred to as the ‘gig economy’, ‘sharing economy’ or ‘free-agent nation’, for a recent survey see Agrawal et al 2015). Online contract labor markets have implications for the distribution of income as well as gains from trade due to de-localizing and offshoring, for example, employers in high-income countries hiring contractors from low-income countries. Here, higher offshoring of information-based tasks – or their potential ‘offshorability’ – seems to be due to more recent technological advances (Blinder 2007). This increasingly affects service jobs, in particular ‘impersonal’ ones that can be delivered electronically with little or no degradation in quality, and do not require workers and services to be co-located. Notably, offshorability becomes less correlated with skills and education over time, at least in the United States (Blinder 2007; Sundararajan 2016). As Bessen (2016) argues, ‘perhaps, the first wave of computer automation targeted ‘low hanging fruit’ in routine-intensive occupations but subsequent innovations may have targeted more valuable opportunities in occupations that perform more abstract [and creative] tasks.’

Online contract labor and crowdsourcing websites such as Upwork, Freelancer.com, Toptal or Amazon’s Mechanical Turk, among many others, globalize traditionally local labor markets. Crowdsourcing makes an ‘open call to an undefined and generally large network of people’ (Howe 2006).

On one hand, online platforms enable employers, frequently those from higher-income countries, to outsource an increasing variety of tasks to contractors, many of whom are located in low-income countries as far as scarce evidence is available on platform activities (Agrawal et al 2015). Notably, work contracts on these platforms are usually offered on a legal work-for-hire basis and on a fixed price or hourly wage basis. However, as regards the general employment status of this new, flexible workforce hosted on platforms, there is an ongoing and heated legal and policy debate inside and outside courts, and it is not limited to the United States (Sundararajan 2016).

On the other hand, online labor platforms already attract millions of users ('contractors') worldwide, many of them freelancers who are diversifying their work and 'topping up' their income with extra project-based work online while keeping their traditional jobs. In the United States alone, lobbying groups estimate that more than a third of U.S. workforce (approximately 57 million people in 2017, up 4 million since 2014) can be considered freelancers in one way or another, with the biggest group of freelancers being 'diversified workers', and 'independent contractors' being ranked as the second biggest category in their series of surveys (Freelancers Union 2017).[5] Estimates by official statistical U.S. sources are typically lower, with results from the Bureau of Labor Statistics (2017) and follow-up surveys by Katz and Krueger (2016) suggest that 'contingent workers in alternative work arrangements' accounted for roughly 15 percent of the total workforce in 2015, up from 10 percent in 2005, even though cyclical effects may bias estimates.[6] Moreover, much contingent work is still happening offline, even when online labor markets seem to be increasing steadily (Freelancers Union 2017). Those "contingent workers" on online platforms only account for 0.5 percent of the total U.S. workforce, and up to 15 per cent of the total U.S. *and* EU workforce, depending on the source and scope of online activities taken into account (Katz and Krueger 2016; Manika et al 2016). Estimates for the U.K. alone suggest that 4 percent of all in employment are working in the gig economy, according to a survey fielded in 2016-17 (Chartered Institute of Personnel and Development 2017 as cited in Taylor et al 2017). Notably, more than half of these gig economy workers are multi-jobbers, engaging in the gig economy on top of more 'traditional' employment. To date, relatively little is known about the composition of workers and the type of occupations involved in online contract labor markets – except that 'digital natives' (those born since the turn of the century and raised actively using digital technologies) seem to be more active there – and whether or not workers with creative skills are disproportionally represented.

The effect of these platforms on the distribution of income is, from an economic perspective, ambiguous and less well researched. On one hand, job-matching platforms could amplify income inequality by way of Rosen's superstar effect (1981), whereby the shift to lower search costs enables employers, in a global rather than a local setting, to identify and contract the best workers, or those workers supplying the best value. In this way, the distribution of the total wage bill would be skewed further towards a minority of contractors. The online feedback systems operated by these platforms have the potential to further increase skewness, even though they may be needed to overcome online information asymmetries and 'make markets' happen (Tucker and Zhang 2007). On the other hand, less mainstream skills in the 'long tail' of the skills distribution – for example, cutting-edge programming in django (specialized web frameworks) – could be matched more efficiently due to more information available on markets, and therefore reduce overall income dispersion (Anderson 2006). Research showing that online sales in books, video and clothing are less concentrated on most popular items than in offline stores points in a similar direction on the demand side of markets (Zentner et al 2012; Peltier and Moreau 2012; Brynjolffson et al 2011).

However, superstar and long tail effects are not mutually exclusive, but may co-exist on platforms as they each operate differently, i.e. focusing on either quality or variety, respectively (Bar-Isaac et al 2012). Accordingly, the contractors likely to benefit from platform participation are: i) vertically differentiated, offering higher quality; ii) horizontally differentiated, offering scarce skills, since demand relative to the supply increases on a global matching level; or, iii) those previously offering at lower cost due to fewer local offline opportunities. However, benefits come at the expense of those with skills that are neither differentiated nor low cost, such as those offering mediocre quality and common skills, often affecting workers residing in high- or middle-income countries.

Overall effects on income inequality are expected to be mixed (Agrawal et al 2015). Although online platforms decrease income inequality as the total wage bill shifts from high- to low-income countries, resulting productivity increases in high-income countries may further increase offline wages there, eventually offsetting the effect of offshoring. At the individual level, while platforms favor highly-skilled contractors, gains from enhanced matching and constrained supply may partially offset increased competition. Accordingly, this might temper the extent to which platforms amplify skewedness of the income distribution at the individual level. At large, as the mainly theoretical literature yields ambiguous implications on the income effects of online contract labor markets, there is a clear need for more empirical work in this area, in particular research that considers online and offline labor market outcomes simultaneously.

What precisely can be learned from the literature on the effects of online contract labor as regards creative and artistic labor markets? Not all jobs posted on online platforms should be considered creative or cultural tasks, nor is all contingent work occurring online. However, Blinder (2007) classified most artistic occupations as ‘offshorable’ – alongside most factory jobs – and a few of them, such as computer programmer, film editor or fine artist, as ‘highly offshorable’. There is early evidence that creative work supplied via platforms is substantial across many countries (Kässi and Lehdonvirta 2016) and does not only cover ‘born digital’ tasks such as software and coding tasks. For example, the main job categories posted on the oDesk platform include design and multimedia, software and web development, and writing and translation: all services that are part of the creative economy (Agrawal et al 2015). At the same time, a number of specialized labor matching platforms have emerged, most of them in the late 2000s, focusing on one or more creative tasks such as design (99designs, designcrowd), coding (elevate), fashion/photography/interior design (creative loft, threadless), writing/translation (gengo), or writing/videography (contently, ehow). Similarly, one of the few works using descriptive data (Sundararajan 2016) suggests that the often observed wage premium for on-demand workers online – when compared to corresponding offline wage rates – does not seem hold for many creative tasks such as graphic design, writing and editing, web design and development. As argued above, it is precisely those creative tasks that do not require the worker to be in the same place where the service is provided.

However, the above argument holds even if markets for creative work are not experiencing a major shift to online matching environments, as any non-art task posted online could provide an additional source of income for artists in order to subsidize their art or art-related income. So, there is a chance that project-based, online labor markets provide more opportunities for creators to further diversify their already flexible work arrangements, and this may better align arrangements with one of their key motivations: to work autonomously. In line with creators’ often positive perceptions of their own independent work arrangements (Caves 2000), more than 80 percent of workers surveyed on oDesk state that flexibility and freedom is an important benefit of working on the platform, and there is some evidence that this freedom contributes to a significant increase in female labor force participation (Dettling 2014).

However, it is hard to assess precisely how this greater flexibility affects labor supply choices and incomes. If anything, there is some reason to believe that entry barriers to artistic markets are falling in due course, as some artists might now be able to subsidize their art work with online non-art work for the first time (and vice versa). Here, as benefits from digital technologies vary by location, locations with fewer offline options in the pre-digital era may benefit more (Forman et al 2012). The downside of online labor markets, however, does not seem to incentivize subsidization via online freelancing, given the high risk associated with pure artistic work at the outset. Minimal or no job security or benefits (insurance, pension schemes, etc.), as is common in online work arrangements, would increase the overall risk of the artist’s occupational portfolio and may hinder its diversification.

Offline sources of income (both non-art and art-related) are typically more secure and entail certain job benefits. From a risk perspective, creators seem more likely to choose higher-risk art work online as a *complementary* source of income if available, or, alternatively, *substitute* art work online for less non-art work offline (as predicted in the Throsby model), at least for those creative occupations eligible in the digital. Note that this does not rely on the presumption that online work is extending overall markets and labor opportunities for artists, but rather is due to different risk profiles associated with online work.

Moreover, screening and reviewing mechanisms governing the matches of supply and demand on platforms impact on the distribution of income (Sundararajan 2016). While user ratings and performance feedback systems may help to decrease information asymmetries online – i.e. they enable sorting high quality types for both contractors and employers, and building reputation – they may also introduce new 'severe information frictions', as argued by Agrawal et al (2016). Evidence shows that even small amounts of employer- or platform-provided information have a large effect on future employment prospects (Pallais 2012; Agrawal et al 2013). This neatly lines up with the 'repeat hiring' patterns observed in many creative occupations and discussed above, and it implies that online work arrangements may further deepen skewedness of income in these superstar-type markets (Bessen 2016). This view is largely corroborated by the anecdotal evidence that many contractor profiles online not only list online testimonies of previous work, but also list offline ones. Moreover, interesting research by Araujo (2013) shows that, on the 99design platform, which operates on a winner-takes-all mechanism, the majority of design contests are dominated by a relatively small number of designers, and a large number of designers are unable to win a single contest. Also, on the individual artist level, career development may be slowing down for many creators as new online learning opportunities are shared among fewer reputable creators and online markets contribute to a greater selectivity in the overall talent discovery processes both online and offline.

However, greater market selectivity may now draw upon a lottery of more geographically dispersed creators, some of them not provisioned with any labor or learning opportunity in the pre-digital world; so, at the same time, it may come along with better labor matches online and higher quality output in some cases,[7] partly because 'decisions by the crowd' seem to complement (offline) expert ones in a meaningful way (Mollick and Nanda 2016). In a similar vein, Aguiar and Waldfogel (2017) argue for a 'random long tail' in the distribution of creative works, due to a strong decline in the costs for generating new works. This may also compensate for some of downsides of selectivity. Simply put, reduction in the cost of bringing new media products to market not only makes it possible for retailers to carry additional products (the so-called online 'infinite shelf space'), but creators can now make more products in the first place. Accordingly, due to generation cost decreases in the digital age, there are 'more draws from a lottery of possible winners, whereas some proportion of these additional draws will deliver some additional high-quality products' (Aguiar and Waldfogel 2017). Generation costs on the side of creators are thus not just an indicator of lower costs for artistic experimentation, but an important determinant of income or net earnings over time (in the common case of the self-employed), with net earnings typically being defined as periodic profits off business expenses, and in particular costs for generating new works.

There is anecdotal evidence on the decline in generation costs in a number of creative occupations. In the pre-digital music world, bringing an album from a new artist to market would cost approximately one million US-dollars, and most releases were not commercially successful (The International Federation of the Phonographic Industries 2010; Caves 2000). Today, musicians can create a good quality recording with an inexpensive microphone and software on a computer or smartphone. For about ten US-dollars, an artist can make a song available on iTunes (Waldfogel 2015), even though promotion is still difficult. Similarly, digitization impacted on generation costs in the movie industry. Since the mid-2000s, the cost of making a distribution-quality movie has fallen drastically, enabling many independent filmmakers to create professional-looking movies (Waldfogel 2016).[8] In this way, across many artistic occupations, digital technologies and the internet have acted as a major cost-decreasing innovation, as the former share many features common to a general purpose (GP) technology.

More broadly, innovation in creative production may be a result of the interaction between new artistic techniques, aesthetic shifts, and market transformations, and thus have implications for labor productivity and supply. As stated in Menger (1999) innovations 'tend to lower or to modify the usual skill requirements, or alter the quantities of input factors in the production process, resulting in an increase of the artists' productivity, a growing competition among them, and a declining control over entry and professional practice through the traditional devices of the professionalization system.' The pop music revolution, the success of dance music or the fast growth of appropriation arts not limited to the visual arts are recent examples of process innovation, which can be partly explained as the result of the widespread availability and lowering cost of technology (Peacock and Weir 1975; Hesmondhalgh 1996). Moreover, even though evidence is scarce to non-existent, there is reason to believe that not only the cost of generation, but also costs for artistic collaboration and networking online have declined over time (Bakhshi et al 2015). These collaboration opportunities may lead to gains in productivity and, eventually, an increase in the supply of co-authored works.

The most iconic example of innovation in the digital age is user-generated content (UGC), with Zhang and Zhu's research on Wikipedia users (2011) standing as a prime example. The emergence of UGC online is very likely associated with the underlying intrinsic motivators for creativity discussed before in this study, i.e. self-accomplishment and utility derived from the creative process itself (Handke et al 2016). Here, generation cost decreases have substantially lowered market barriers and seem to have led to mass entry supply of amateur creators or 'prosumers' (a neologism for consumers who have become producers of content themselves). Arguably, this also applies in certain areas of the creative economy. Studies, such as the U.K. IPO's commissioned studies (2013) on parody and pastiche reusing existing works, show that UGC activity generates considerable commercial value, and it does not need to economically damage incumbent right holders. In this specific case, a small but growing market for skilled UGC had emerged in the UK and generated up to two million British Pounds in revenue for Google and parodists in 2011. Even though it may be hard to draw the line between amateur and professional creators and their activities, a small fraction of the total UGC works may later take on monetary value that is paid for (Handke et al 2016; Hargittai and Walejko 2008). Moreover, assuming that certain amateur generated material is 'donated' to markets as it is motivated by altruistic behaviors and social preferences of creators (see above discussion), amateur works may cannibalize sales and profits by professional creators. This phenomenon well known in development economics as 'killing entrepreneurial spirit' (for example, Hansen 2004). Therefore, we hypothesize,

> **#2** If costs for the generation of new works *decrease* on the level of the individual creator, labor supply in creative occupations *increases* as fixed-cost barriers to these markets are lowering.

Empirical strategy and methodological challenges

The core objectives of our observational study are to carefully inspect and document regional and global time trends since the turn of the century in, a) the supply of creative occupations labor, b) income levels and, c) distribution of income, and verify these trends on the basis of various national and international data sources. In this way, this study does not attempt to identify underlying causes that ultimately change the supply and income patterns we observe over time; hence, credibly establishing causality of determinants/factors, in particular those trends related to digital change, is left to future research.

We use multivariate and descriptive analysis to illustrate time trends in income levels. In a multivariate setting, we process the data in the following way: for most models and cross-sectional data sources, we compare income deciles (more specifically, deciles' upper values) in the treated group of identified creators to deciles observed in a control group, while accounting for a number of context- or country-specific factors such as GDP variation, and, in other instances, socio-demographic characteristics such as gender. As a control group we select total sample observations, i.e. the total population, if not specified differently in estimation models. Next, we test for significances in differences of estimated time trend coefficients for treated and for control groups ('F-test'). Where feasible and data are available, we run separate regressions and identify time trends differences for the supply of creative occupations labor (approximating 'equilibrium' supply via the total number of artists entering markets as identified in the various data sources), and also for the levels of income concentration (for example, we calculate Gini indexes to approximate the changes in income distributions over time).

Common methodological concerns in quantitative studies of artists and creators are their identification in the data and, more broadly, whether data samples are representative of the total population of artists and creators. Clearly, there is no *a priori* right definition of artists (Bille and Lorenzen 2008, Frey and Pommerehne 1989), and, again, choices of reference populations may influence results. Hence, we verify our results on time trends and tackle most of these concerns by using a variety of data sources that we describe in the next section, and by using different criteria to identify creators and delineate control group observations in the data ('triangulation').

Many creators cross-subsidize their income via working multiple jobs, working in non-art occupations, or by relying on spouse's income. So, in line with most of the literature, art labor supply choices also depend on the creator's ability to cross-subsidize and diversify/pool his or her income risk. Accordingly, household-level information on income is preferable over individual-level, if such information is available in the data. Similarly, data that allow monitoring income and supply from all jobs of multiple job holders as well as categorizing information on these jobs into art and non-art is advantageous. In turn, data that do not categorize jobs in such a way – for example, data that are limited to first-job information, or job information being available only for a specific person in the household (the survey respondent, head of household etc.) – introduce certain bias to the analysis. Such bias may affect identification of creators in samples and, ultimately, the art labor supply choices observed.

As discussed before, artists derive value and satisfaction from their work in a variety of ways aside from income, and it may well be that overall satisfaction encourages further creativity. In this way, creators' utilities and 'psychic income' from their work can be measured, for example, via their job satisfaction scores (Steiner and Schneider 2013). Accordingly, we do not limit data search to more widely-used sources surveying individuals or households on income, but extend to alternative sources that also monitor job and income satisfaction levels.

Data sources

First, we identify creators from annual data on population-wide, gross household income distributions for a set of countries and using a specific set of occupational categories (for the set of countries and the 4-digit level, International Standard Classification of Occupations (ISCO) codes, please refer to tables A.1 in the annex). Generally, ISCO codes structure and classify tasks and duties undertaken in the job in meaningful groups. This allows systematic identification of non-routine, creative tasks at the level of the individual worker, and also allows the exclusion of 'humdrum functions' among all creative economy jobs such as technical support (Caves 2000). Occupational classification has been used in previous research[9] on the creative economy and has been fairly consistent over the period of observation we are interested in, which is one of its pros when compared to industry codes. More concretely, the occupations we identify as relevant include visual artists, authors and writers, actors, musicians, singers and composers, designers, photographers, but also architects, IT developers, advertisers and journalists.

Here, the main data source is the Luxembourg Income Study (LIS) database. The database aggregates and harmonizes data from national census, household and labor force surveys, with an emphasis on middle- and high-income countries. However, for the purpose of this study, we develop several co-classifications bridging structural breaks in ISCO classifications (88-08), as well as ISCO codes and codes from proprietary national classifications in cases where ISCO codes were not available in the LIS data (again, please refer to tables A.1 in the annex). Occupational codes are available for the first and second jobs of any household member recorded in the data, with very few exceptions.[10] Moreover, for the United States, we complement the LIS data with data from the Integrated Public Use Microdata Series (US IPUMS) which offers better coverage for the period we are interested in, and also 'winsorize' underlying earnings distribution in order to limit effects from outliers on inequality measures, i.e. carefully bottom- and top-coding data.[11]

Household income, as we define and gather the LIS and IPUMS data, contains 'gross total income including public and private transfers'.[12] Notably, given that the sample sizes in some of the selected countries are low, the data do not allow to separate out or distinguish for individual sectors of the creative economy, for example, income levels and labor supplies in music or audiovisual sectors. However, standardized household weights in the LIS data allow us to generate 'true' population estimates/representative values based on the samples. The definition of self-employment we implement in the analysis of the data is relatively broad: it always excludes 'dependent employed' and 'regular employees', and it allows for individuals – in particular creators – to also hold other atypical working arrangements such as 'non-regular employee'. Our final data covers the period from 2002–2014 and consists of an unbalanced panel of countries using surveys from Brazil, Germany, Denmark, Estonia, Mexico, Russia and the United States, with very few exceptions.[13] Table A.2 in the annex summarizes the data. The selection of countries and restriction to data from certain years are mainly driven by various data comparability issues and relevant information being available at sufficiently granular levels.

Second, we deploy microdata from the European Value Survey (EVS) waves using the same 4-digit ISCO codes as in LIS in order to identify creators. The data provides us with information on monthly gross household income and job satisfaction levels and socio-demographic characteristics for survey respondents from a set of EU member and accession states. Data availability of EVS is limited to the survey's third and fourth waves only (1999–2004, 2008–2014), and, again, the data do not allow for separation of individual sectors. Moreover, occupational codes are only available for the survey respondent's and not the spouse's main job. However, for Europe as a region, it covers a substantially larger set of countries when compared to LIS,[14] and the satisfaction survey items on a Likert scale[15] allow us to proxy psychic income levels for treated and control groups. Table A.3 in the annex summarizes the data.

Third, alternatively, creators self-identify as those that chose formal artistic tertiary education in the United States, and so we use several large survey waves among alumni from U.S. music and art schools. Surveys are commissioned by the Strategic National Arts Alumni Project (SNAAP), and their research focuses on improving schools' training quality and students' educational experiences. Among many other items, surveys request annual information on gross income bands and job satisfaction from alumni.[16] Moreover, they carefully document the occupations in which respondents spend the majority of work time and, in the case of multiple job holders, information on other occupations held. Previous research has used this source of unique data and offers a more detailed view on the way the survey is implemented and run (Fosnacht et al 2017; Lambert and Miller 2014; Kennedy et al 2010). We limit our sample to the 2010 to 2015 data waves (for 2013, no data have been collected), and this time we are able to distinguish artists with different majors, i.e. we can separate out discipline-specific income patterns. In the SNAAP data and in contrast to the standardized ISCO coding used in LIS and EVS, alumni hold majors in a variety of fields, namely, architecture, art history, arts administration, art education, creative and other writing, dance, design, fine and studio arts, media arts, theater, music or craft fields. One caveat of the data is that SNAAP surveys do not capture U.S. based creators that are self-taught (Alper and Wassall 2006). Table A.4 in the annex summarizes the data.

Finally, creators self-identify when participating in a targeted social insurance scheme for self-employed artists living in Germany, making revenue from self-employment and faithfully reporting the latter to tax/insurance authorities. Among other things, records from the insurance scheme ('Kuenstlersozialversicherungskasse' or KSK) include individual-level annual income/net revenue averages from their artistic/publistic and self-employed work, with creators being required to report income to KSK authorities once they participate in the scheme. Launched in 1983, the basic idea underlying KSK is to offer self-employed creators an insurance scheme with similar benefits and public co-financing of insurance costs[17] as those available or obligatory to those working in regular employment, where costs are co-financed by employers. Furthermore, the data allow the categorization of creators by artistic discipline/type of work, namely, fine arts, performing arts, music and writing/literature, as well as their career stages and socio-demographic factors such as gender. Again, this differs from the standardized ISCO coding used in LIS and EVS. The unique KSK sample covers the observation period from 2002 to 2017, but, again, data are restricted to self-employed artists living in Germany. Table A.5 in the annex summarizes the data.

We also considered and reviewed several other candidate sources such as the EU's Labor Force Survey (LFS), Statistics on Income and Living Conditions (SILC) and the Structure of Earnings Surveys (SES). LFS data, however, does not provide information on the earnings/profit situation of self-employed persons, and self-employment as a flexible work arrangement is commonly observed in many creative sectors. Sample sizes are relatively small in the SILC data and data collection only began as late as in 2003. The SES data has limited coverage over time as it is only run every four years. In general, criteria for selection of data are sources' international data coverage as well as data availability and comparability over time.

RESULTS

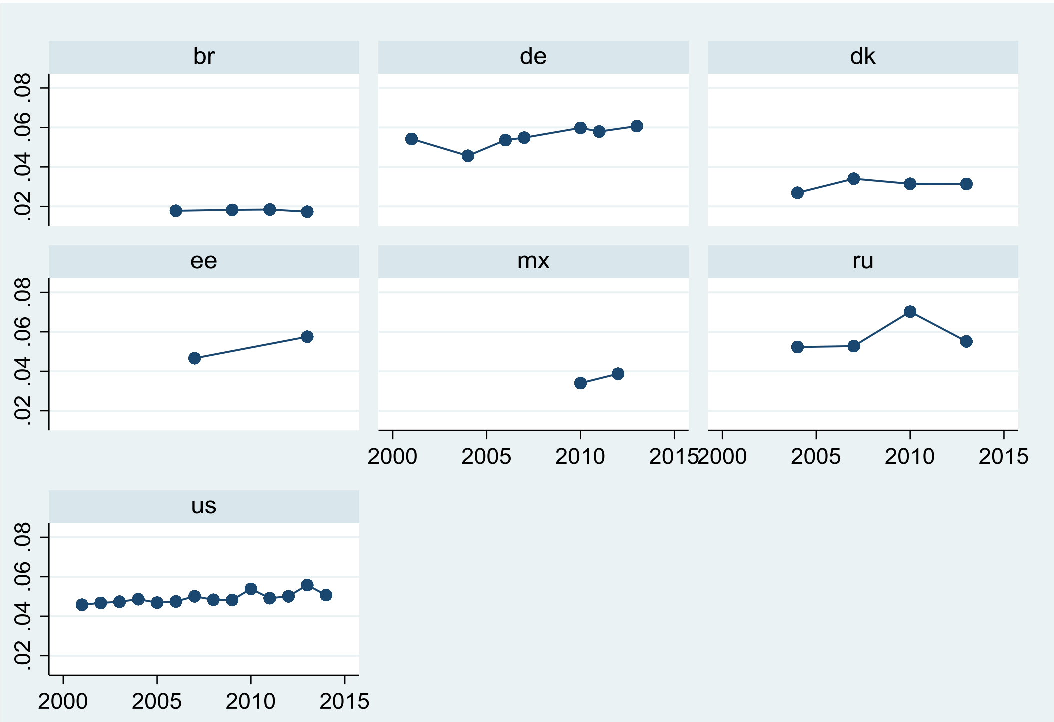
Time trends in income levels, income distribution and labor supply in creative occupations – evidence from census, labor force and household surveys worldwide

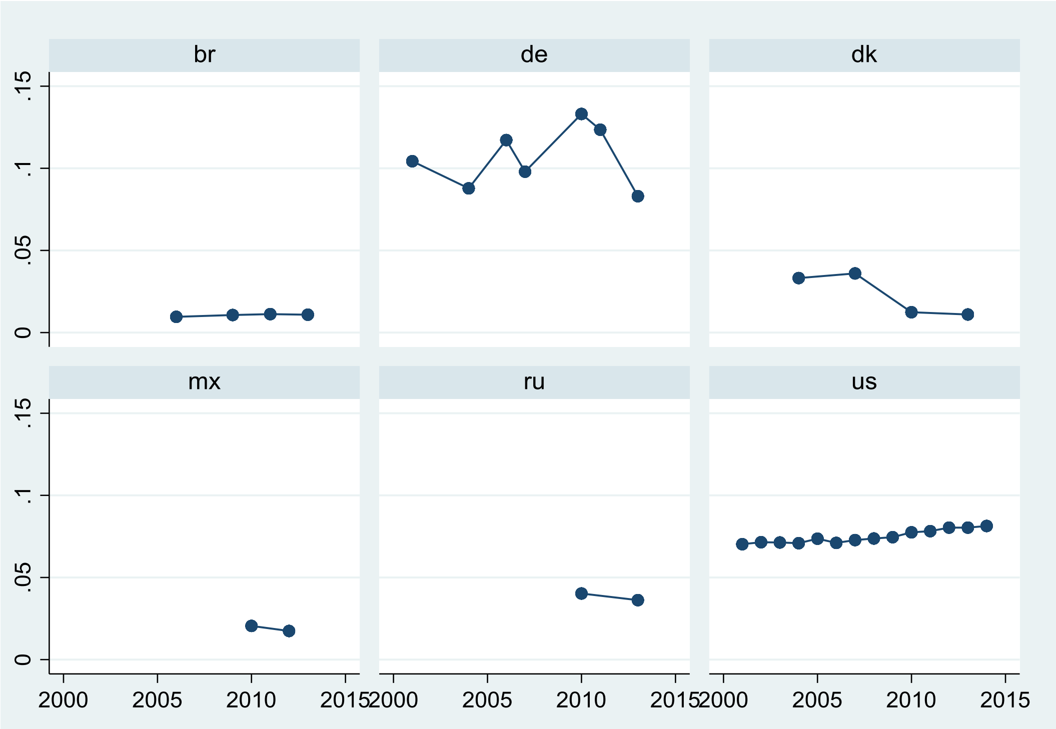
This section's analysis builds on income statistics retrieved from the Luxembourg Income Study (LIS) database and identifies creators via their occupations as recorded in large-sale national surveys (for details on identification and data please refer to the dedicated data sources section).

As a first step, we descriptively study labor supply in creative and other occupations in a number of selected economies and for the period of observation (2002–2014). The evidence (graph 1, top) suggests that shares of creator households – i.e. households with one or more members identified as a creator - in the total number of domestic households have been weakly increasing in most countries, with shares ranging between roughly 2 and 7 per cent. Such trends are indicative of the generation cost decreases and lowering barriers to entry for creators in the digital era. Moreover, they are in line with the general argument made by Baumol and Bowen (1966) on cost diseases in the arts and in other labor-intensive services, i.e. these services are attracting more workers while decreasing in their labor productivity relative to most other sectors.

For a subset of the data including only households with one or more self-employed member (graph 1, bottom), creator households are overproportionally represented among the total self-employed. However, when based on these self-employed samples, the descriptive evidence on time trends in labor supply is less straightforward and in fact ambiguous. In some countries, such as the United States, creators' relative labor supply among the self-employed is increasing; in others, such as Denmark, it is decreasing over time.

Graph 1: Share of households with one or more creators in the total number of national households, overall sample (top) and self-employed work status samples (bottom)





Source: Based on author calculations and LIS/IPUMS data. Note: For self-employed individuals, limited or no data available for Russian, Estonian and German samples.

As a second step, we econometrically study time trends in income levels of creator households in a multivariate setting (table 1). Model specifications 1 and 2 are based on the overall sample, while specifications 3 to 6 are based on a subset of the data focusing on self-employed only. Moreover, 3 to 6 serve as robustness checks and are expected to increase homogeneity of samples, i.e. the idea is to compare creators (or subsets) to groups of similar occupational and professional standing. Again, individual data points represent upper values of deciles in annual, ppp-adjusted (international US-Dollars with reference year 2011) household income distributions data collected for each country. We deploy logged income decile values as dependent variable and insert a 'time' trend variable, aggregating the years passed since 2002 as the main independent variable. Moreover, total population households are used as a control group which allows us to benchmark income time trends observed among 'treated' creator households and study general group differences. For example, in the U.S. case, this results in 10 deciles values per year, times 14 years over the observation period, times 2 groups (treated and control), or a total of 280 observations for the U.S. alone. We add decile and country fixed effects to each model specification as well as logged real GDP in constant 2010 US-Dollars, accounting for economic cycle effects. Furthermore, we segregate effects for treated and control groups by separately estimating coefficients for our main time variable and several control variables (specifications 2, 4 and 6). Specifications 3 and 4 differ from 5 and 6 only as far as the latter two include and log a proxy/control for the 'equilibrium' supplies of labor, i.e. the weighted total number of households in each group.

We find significant negative time trends in income decile levels for all model specifications. However, based on specifications 2 and 4, and disaggregating these overall trends, income decreases over time only in the control group/total population, while income stagnates in the group of creators. Statistical tests confirm that the two time trend coefficients do indeed systematically differ as tests are significant (F-tested, (2), Prob>F=.0119, (4), Prob>F=.0034). This suggests that creators were able to improve their relative income position over time compared to income in the total population. Results in specification 6 are exceptional as income trends in both groups turn negative, but tests on differences of coefficients render insignificant. However, estimates in this last specification might suffer from an endogeneity bias as wages and supply of labor are simultaneously determined.

Please note that results on time trends are sensitive to the inclusion and 'benchmarking' of time trends on real GDP variables as economies/GDP seems to be growing faster than real wages. Once we do not include real GDP to equations, overall trends render insignificant or even positive in most specifications (please refer to table A.6 in the annex), in line with previous research by Piketty and others showing that real wages are stagnating over time and across all occupations (for example, for the United States, Piketty et al. 2018). But even then our results do confirm that creators are relatively better off as concerns their income time trends.

Furthermore, in table 1, it must be noted that there is ambiguous evidence on income levels (i.e. 'creator sample' dummy coefficients) and absolute levels seem sensitive to specific control group choices, largely in line with previous research outcomes. Specifications 1 through 4 suggest an income 'premium' for workers in creative occupations when compared to workers in the total population. Specifications 5 and 6 imply an income 'penalty' among those self-employed in a creative occupation when compared to all self-employed in the total population, but once again, these estimates might suffer from an endogeneity bias.

Table 1: Estimation results (OLS) and robustness checks reporting coefficients and standard errors for income levels, by any work status and by self-employed only

Sample	**any work status**		**self-employment only**			
Variable	**DV: log household income**		**DV: log household income**			
Model	(1)	(2)	(3)	(4)	(5)	(6)
time	-0.010***		-0.013**		-0.024***	
	0.003		0.005		0.003	
time (total population)		-0.015***		-0.020***		-0.023***
		0.003		0.005		0.003
time (creators)		-0.006		-0.006		-0.028***
		0.003		0.005		0.003
creator sample	0.620***	1.735***	0.244***	1.739***	-0.735***	-2.380***
	0.012	0.2	0.017	0.367	0.044	0.373
log real GDP	1.326***		0.711**		1.300***	
	0.137		0.252		0.181	
log real GDP (total population)		1.347***		0.740**		1.382***
		0.132		0.245		0.151
log real GDP (creators)		1.305***		0.683**		1.379***
		0.132		0.245		0.154
log number of households					-0.318***	
					0.014	
log number of households (total population)						-0.454***
						0.015
log number of households (creators)						-0.348***
						0.017
decile FE	yes	yes	yes	yes	yes	yes
country FE	yes	yes	yes	yes	yes	yes
const.	-20.740***	-21.298***	-9.381	-10.128	-21.790***	-22.079***
	3.246	3.128	7.615	7.403	5.425	4.538
N	630	630	558	558	558	558
Adj. R2	0.972	0.974	0.953	0.956	0.977	0.984

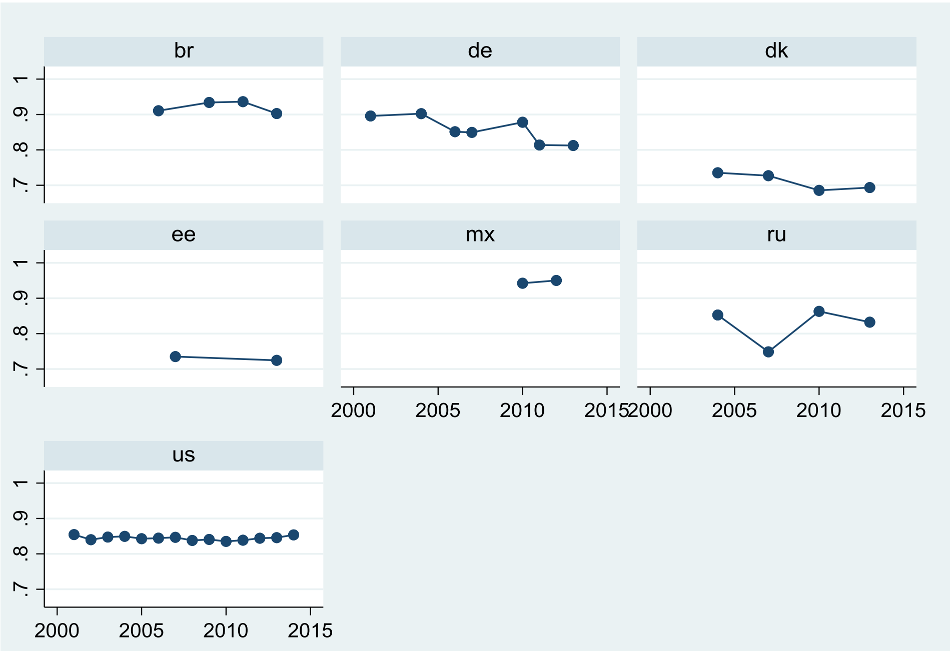
legend: * p<.05; ** p<.01; *** p<.001

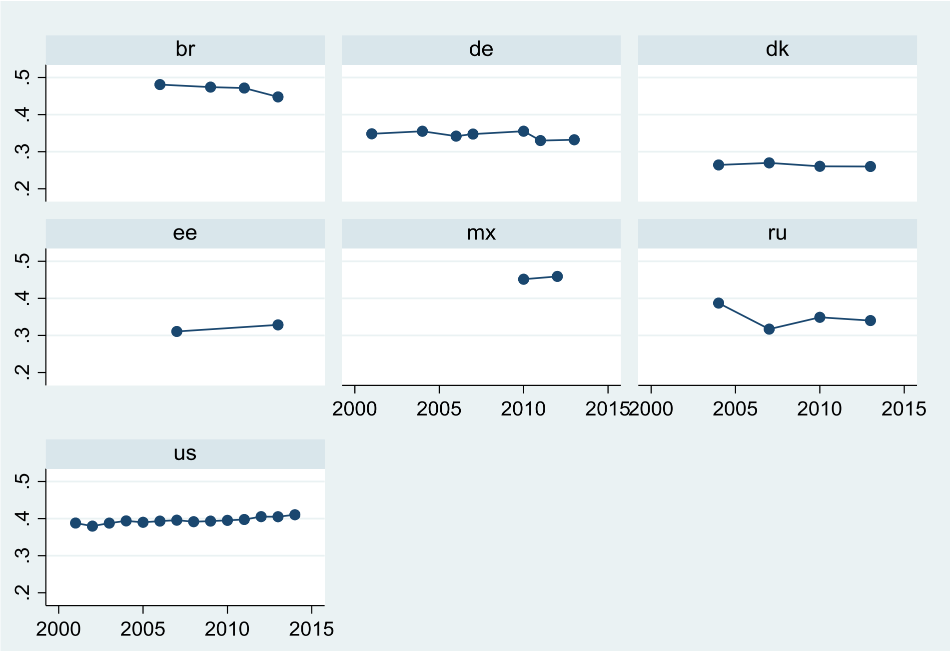
Source: Based on author calculations and LIS/IPUMS data. Note: For self-employed individuals, limited or no data available for Russian, Estonian and German samples.

As a third and final step in the LIS data analysis, we descriptively study changes in distributions of income over time (graphs 2 and 3). We approximate levels of concentration in distributions by calculating Gini index values on the basis of the LIS micro datasets for each sample, country and year, higher index values being associated with higher levels of concentration. Concentration levels vary by country and stages of overall economic development of a country seem to be associated with the variation of levels observed. Further, in absolute terms, income dispersion seems more pronounced for self-employed than it is in each country's total population, where respective Gini index values are typically lower (graphs 2 and 3, bottom). This confirms intuitions from the previous literature on earnings structure, in particular entrepreneurial research.

It is interesting to note that income in creative occupations is commonly less concentrated than income in the total population (graph 2, top), i.e. most Gini ratios/data points range below 1. In certain countries, such as Germany, this 'gap' has been widening with creative occupations income becoming more evenly distributed over time, both in relative and absolute terms. However, this time trend does not seem to apply across countries and so warrants a country-by-country analysis of concentration levels. For example, in the United States, income concentration levels for creative occupations workers seem to be stagnating over time when compared to the total population's Gini index. At the same time, concentration levels are very weakly increasing in absolute terms.

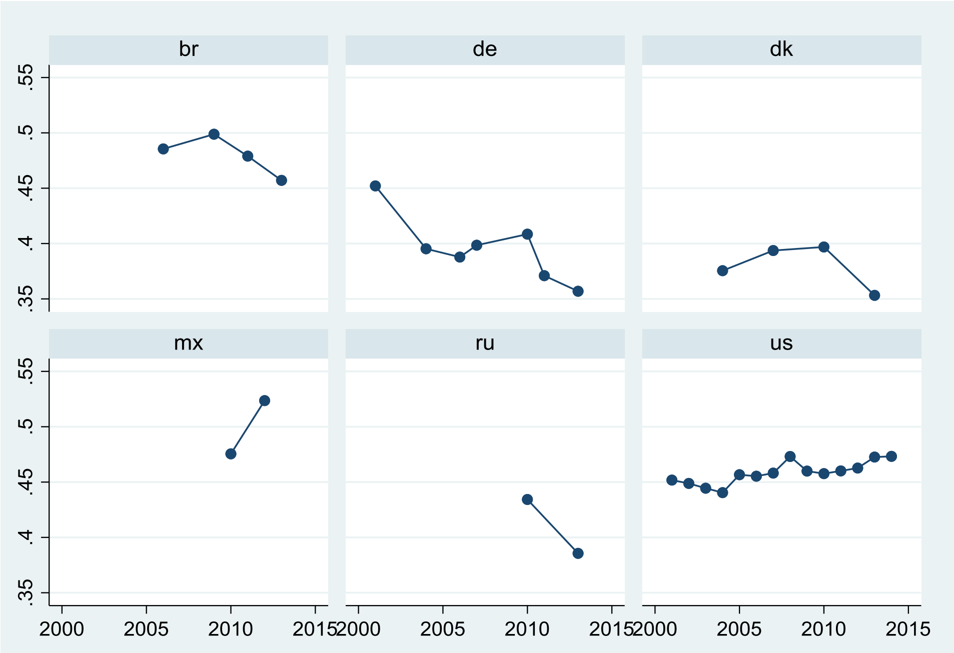
Graph 2. Income distribution in all creative occupations, Gini values relative to total population ones (top), and absolute Gini values (bottom)





Source: Based on author calculations and LIS/IPUMS data.

Graph 3: Income distribution in self-employed creative occupations, Gini values relative to self-employed total population (top), and absolute Gini values (bottom)



Source: Based on author calculations and LIS/IPUMS data. Note: For self-employed individuals, limited or no data available for Russian, Estonian and German samples.

Overall, results based on the LIS data do lend some support to the wage implications from skill-biased technological change theories (Acemoglu and Autor 2011), even though we do not explicitly model and take into account demand changes. These theories expect expanding IT automation and offshoring to create favorable income level trends for those working in creative occupations, as their skills are more heavily in demand. Arguably, we also notice weak increases in the total supply of creative occupations labor in most countries, which may counteract some of the wage effects on creators and relative income gains. Weak increases in the total supply of creative occupations labor are also indicative of generation cost decreases in the digital age, which may have lowered market barriers and induced more creative workers to entry, and, à la Baumol, causing workforces to transition to low-productivity services.

Alternative data sources and metrics – evidence from European value surveys, German insurance and United States graduate data

I: EVS data

The section's analysis builds on data and individual responses from the European Value Surveys (EVS), in particular survey waves 3 (1999–2001) and 4 (2008–2010). As in the LIS analysis, we identify creators via their occupations, but vary the selection of occupational codes (for details on identification and data please refer to the dedicated data sources section). Moreover, in the EVS analysis and in addition to income, we assess time trends on the basis of a different metric, i.e. 'psychic income' as approximated by job satisfaction, and, of course, on the basis of a different data source and a slightly different set of countries.[18]

As a first step, we descriptively study the supply of creative labor. Across countries and waves, those working in creative occupations account for approximately 2.5 percent of total survey respondents (EVS samples being representative of countries' adult populations). From wave 3 to 4, shares increase from approximately 2 to 2.8 per cent. For the subset of self-employed, self-employed in creative occupations are over-represented among all self-employed with close to 8 per cent.

As a second step, we econometrically study time trends in income and job satisfaction levels in a multivariate setting (table 2). Model specifications 1 and 3 use logged, ppp-adjusted and deflated (base year is 2010) monthly household income as a dependent variable, while specifications 2 and 4 replace the latter by job satisfaction levels as measured on a ten-point Likert-scale. In all specifications we use ordinal least squares treating the DV with its many categories as if a continuous variable. However, results remain largely unchanged when, alternatively, we opt for an ordinal logistic regression in specifications 2 and 4.[19] In addition, we include income as a determinant of job satisfaction/independent variable in latter specifications.

For specifications 1 and 2, we use the same set of ISCO/occupational codes as in the LIS data analysis. However, for specifications 3 and 4, we restrict these codes to a core subset, excluding several occupations, such as designers, advertising professionals and IT/web developers (see table A.1 in the annex, printed in bold). These robustness checks suggest that main results do not heavily depend on the selection of codes as they are very similar to those yielded by specifications 1 and 2.

As in the LIS analysis, we then segregate effects for treated (creators) and control groups (adult/total population) by separately estimating coefficients for the time trend variable and several controls we add to all models. Next to country-fixed effects, these controls include, among other, socio-demographic factors such as survey respondents' age, gender, work and household status.[20]

We find significant negative time trends in income levels for specifications 1 and 3 and when comparing levels in survey waves 3 and 4 and benchmarking on GDP trends. Similarly, job satisfaction levels – as an alternative metric to income – shows similar effects in specifications 2 and 4, with workers in creative occupations and workers elsewhere becoming less satisfied with their jobs over waves. However, F-tests confirm that trends in both groups do not systematically differ for income and for job satisfaction levels. This is also the case when we exclude GDP controls from all specifications and our trend estimates remain unchanged or even render positive in both groups (please refer to table A.7 in the annex). Across all specifications, this suggests that the relative position of creators in income terms is not changing over time.

Furthermore, in specification 2, we find very preliminary evidence for a ‘satisfaction premium’ (creator sample variable) in creative occupations, an issue more extensively studied elsewhere in the literature (Bille et al 2013; Steiner and Schneider 2013). As previously discussed, this premium might be due to procedural utilities or reputational rewards, and it confirms that artists and creators also derive substantial utility from non-pecuniary sources, as income can only partially explain variation in satisfaction levels (for further discussion of the issue, please refer to the literature review and to a companion paper to this report, Miller and Cuntz 2018). To be clear, this is not to say that pecuniary rewards do not matter to creators, as evidenced in the literature (Liebowitz and Zentner 2018).

Graph 4 visualizes the satisfaction premium for workers in creative occupations, and it suggests that increases in income levels (deciles) are not associated or are less strongly associated with increases of satisfaction levels (mean) in this group. This holds true for different choices on the selection of occupational codes (using all ISCO codes in the top graph, core ones in the bottom graph). Of course, some of the variation in satisfaction levels is due to smaller sample sizes. Notably, we find no evidence in specifications 1 and 3 for either an income premium or an income penalty in these occupations based on the EVS data.

Table 2: Estimation results (OLS) and robustness checks reporting coefficients and standard errors for income and job satisfaction levels, by all and core occupational codes

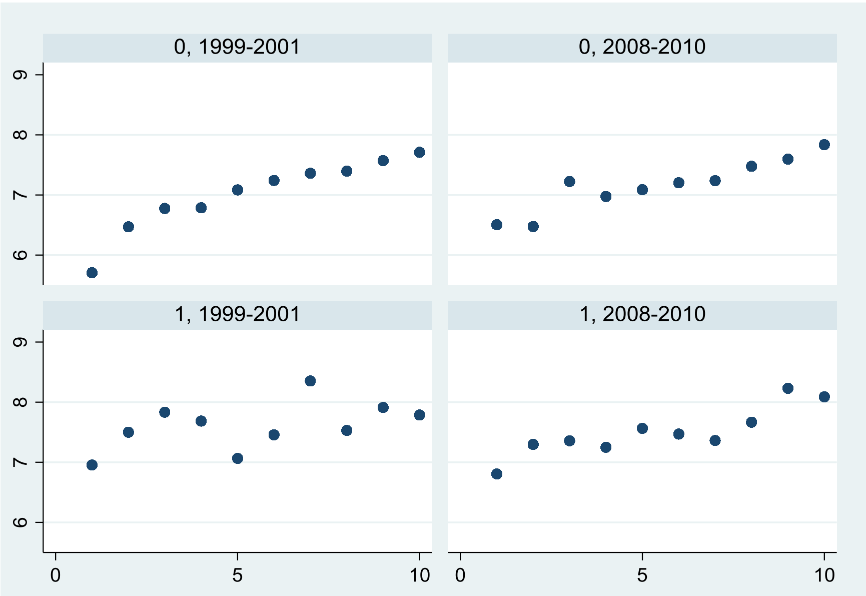
Sample	**all ISCO codes**		**core ISCO codes**	
Variable	**DV: log household income**	**DV: job satisfaction**	**DV: log household income**	**DV: job satisfaction**
Model	(1)	(2)	(3)	(4)
time (creators)	-0.332***	-0.446**	-0.401***	-0.477*
	0.044	0.162	0.056	0.209
time (total population)	-0.391***	-0.162*	-0.386***	-0.167*
	0.015	0.067	0.015	0.067
creator sample	0.022	3.241*	-0.059	3.753
	0.365	1.379	0.506	1.997
log income (creators)		0.352***		0.272*
		0.09		0.118
log income (total population)		0.404***		0.407***
		0.024		0.024
self-employed (creators)	-0.02	-0.121	0.007	-0.195
	0.054	0.187	0.074	0.257
self-employed (total population)	0.176***	0.415***	0.178***	0.397***
	0.016	0.054	0.015	0.053
female (creators)	-0.06	0.201	-0.056	0.362
	0.042	0.155	0.054	0.203
female (total population)	-0.116***	0.01	-0.119***	0.008
	0.007	0.03	0.007	0.03
age (creators)	-0.010***	0.006	-0.012***	0.013
	0.002	0.007	0.002	0.009
age (total population)	-0.014***	0.006***	-0.014***	0.006***
	0	0.001	0	0.001
single hh (creators)	-0.233***	-0.165	-0.340***	0.111
	0.051	0.181	0.07	0.249
single hh (total population)	-0.294***	-0.095*	-0.292***	-0.102**
	0.009	0.039	0.009	0.039
log real GDP (creators)	1.506***	0.739***	1.505***	0.715***
	0.04	0.179	0.042	0.186
log real GDP (total population)	1.504***	0.845***	1.500***	0.851***

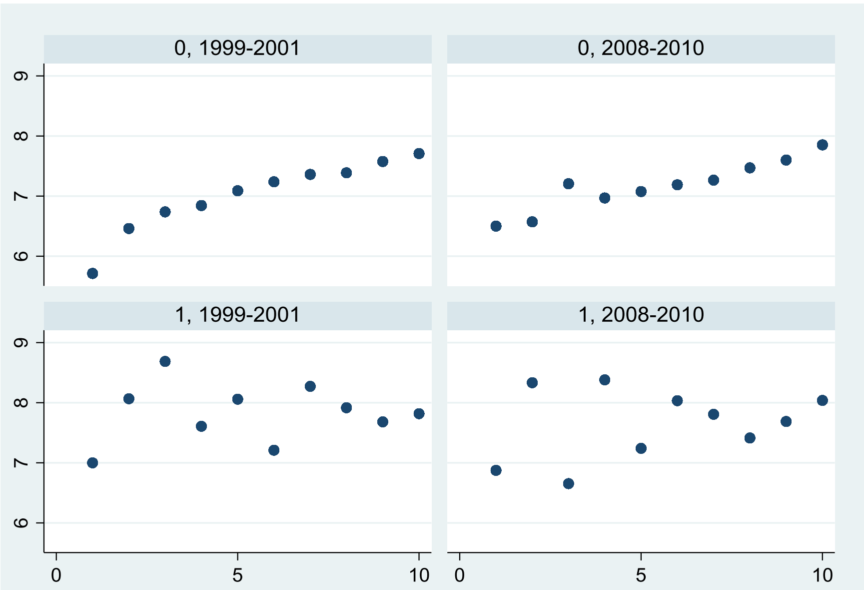
	0.038	0.171	0.038	0.171
country FE	yes	yes	yes	yes
Const.	-35.087***	-13.135**	-34.972***	-17.270***
	0.888	3.995	0.889	4.878
N	38546	20180	38546	20180
Adj. R2	0.549	0.055	0.547	0.055

legend: * p<.05; ** p<.01; *** p<.001

Source: Based on author calculations and EVS data.

Graph 4: Mean job satisfaction by income decile, by workers in creative occupations (1) and total respondent population (0), by waves 3 (1999–2001) and 4 (2008–2010), and by selection of all (top) and core occupational codes (bottom)





Source: Based on author calculations and EVS data.

At large, evidence from EVS does not lend support to the idea of skill based technological change across the mostly European countries covered by the surveys. This differs from previous LIS results. Deploying different metrics and occupational codes further corroborates EVS results. As in the LIS data, we find weak indications that entry is increasing over waves, due to decreases in creators' generation cost as well as transitioning to low-productivity sectors.

II: SNAAP data

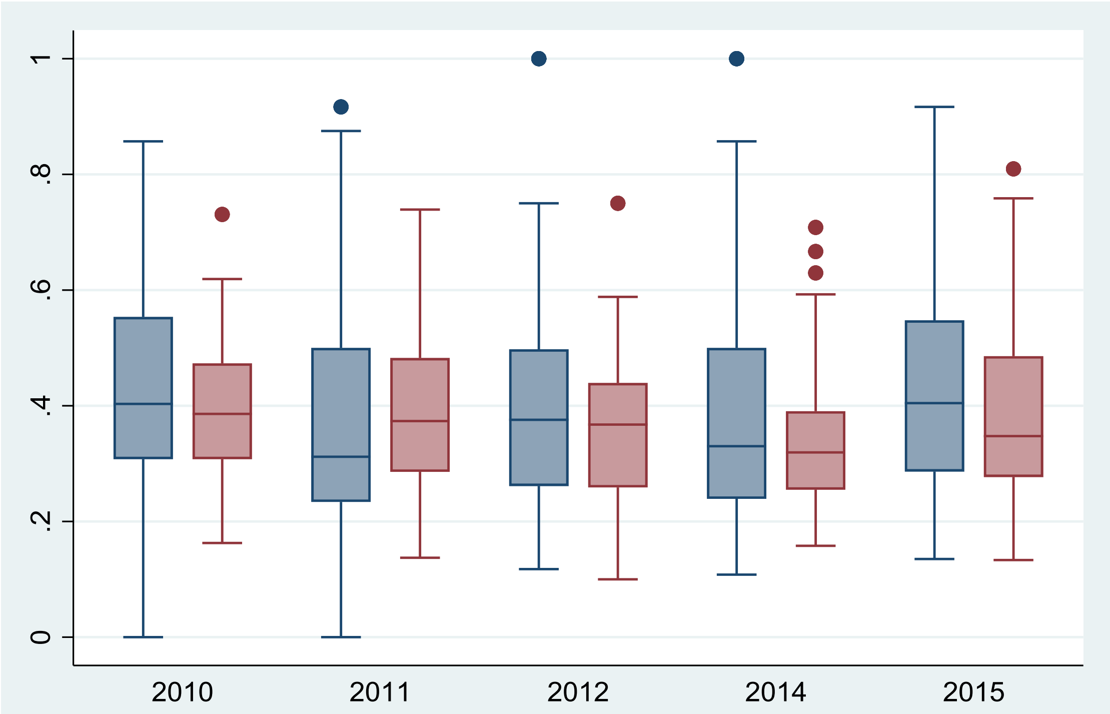
In this section, the analysis rests on unique data from the Strategic National Arts Alumni Project (SNAAP), surveying alumni from a representative sample of U.S. art and music schools in 2010–15 (except 2013). Alumni self-identify as artists and creators earlier by self-selecting into majors or fields of study.[21] Income data are available on bands and on individual levels only and not on household level as in previous datasets. However, SNAAP data enable us to account for creators' cross-subsidizing or substituting with non-art work occupations as an alternative mechanism used by creators to disperse their income risks, different to the risk sharing on household levels. Importantly, the data also allow us to distinguish research outcomes for the various art-related major fields and for graduate cohorts. Arguably, the former also gives us an indication of the changes in sectoral income distributions in the creative economy, at least in the United States.[22]

As a first step, we descriptively study creators who cross-subsidize or substitute with work in non-art occupations and its wage implications, for example, a person with a major in dance working as an engineer (a 'non-art' occupation'), and not as a dancer (an 'art' occupation), and not as a teacher in the arts (an 'art-related' occupation). This distinction of occupations has been used in previous empirical research on the work-preference model (Rengers and Madden 2000). Moreover, SNAAP surveys ask alumni for the occupation in which they spend the majority of their work time (multiple job holders), or their current occupation if only one job is held.

For specific income band levels, specific majors held and years, graph 5 presents the variation in shares where respondents work in non-art occupations as compared to those working in any type of occupation. Here, an average of close to 40 percent report non-art occupations work in any survey year, with average cross-subsidizing rates (or substitution) being slightly higher for workers with higher pay ('upper income band').

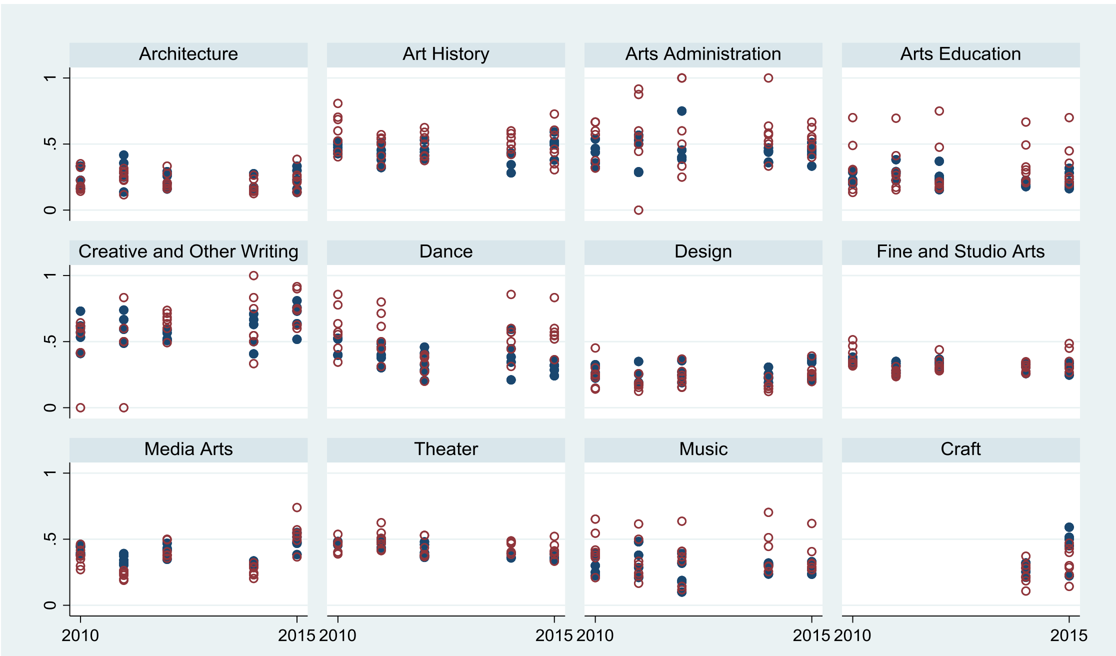
Graph 6 gives similar accounts on cross-subsidizing rates and wages, but further distinguishes the data by major fields. Majors with the highest rates seem to be 'creative and other writing', 'arts administration' and 'dance', even though some of the variation we observe there might be driven by lower sample sizes, in particular lower number of observations in higher income bands. As one might expect, fields with the lowest cross-subsidizing rates are 'architecture' and 'design', as most alumni of these disciplines go on to work in occupations matching their field of study.

Graph 5. Box plot for the fraction of non-art occupations in total occupations held by U.S. art and music school graduates in a specific income band level, major and year, by lower and upper income bands (below/above median income band in red/blue boxes), and year.



Source: Based on author calculations and SNAAP data.

Graph 6: Fractions of non-art occupations in total occupations held by U.S. art and music school graduates in a specific income band level, major and year, by major, lower and upper income bands (below/above median income band in red/blue dots), and year



Source: Based on author calculations and SNAAP data.

As a second step, we econometrically investigate time trends in income levels (model specification 1) and in income polarization (2) for worker in art or art-related occupations. Notably, in table 3, the alternative control group now is workers in non-art occupations within the same major and year and their income, while before we compared trends among 'treated' workers in art occupations to total population ones. We insert major dummies/fixed effects and deflated real GDP with reference year 2010 in both equations. Again, we use ordinal least squares treating the DV with its many income bands as if a continuous variable. However, results remain largely unchanged when we opt for an alternative, ordinal logistic regression for specifications 1.[23] In specification 2, we approximate income concentration across bands by calculating several entropy measures ('normalized entropy'), suitable for categorical data and bounded by 0 and 1.[24] In contrast to the standard Gini index one, higher values for this measure are associated with lower levels of income concentration, i.e. a more equal distribution of income.

As concerns income levels in the United States, we find negative time trends in treated and in control groups when we benchmark trends on economic growth. F-tests reveal that there is a decline in individual wages over time among alumni working in art occupations that is statistically significant and slightly stronger – in terms of the size of the effects – than for those working in non-art occupations. Table A.8 in the annex confirms the result and its basic intuition. Non-art occupations are also slightly better off for a set of estimations that do not include real GDP controls. Here, wages in non-art occupations are increasing at a higher rate than those paid in art occupations.

Fixed effects coefficients of majors suggest that workers in architecture, design, media arts, theater and music, in general, are better off from a wage-level perspective during our observation period than those working in creative and other writing, dance, or fine and studio art. In contrast to what the descriptive analysis suggests, we do not find evidence for an income premium from non-art occupations work in the multivariate setting.

As concerns income concentration, we do not find a significant time trend on the basis of the U.S. focused SNAAP data. However, in line with some of the literature on superstar labor markets, we do find some evidence for less concentration in income earned in non-art occupations than for income distributions in art occupations ('non-art occupation' dummy variable in specification 2). Also, concentration of income differs across major fields (please refer to graph 7 for an illustration of changes over time), and income in architecture, design, media arts, theater and music is more equally distributed than elsewhere. Notably, less concentrated fields tend to coincide with those that also recorded higher income levels.

Finally, the explanatory power of model specification 2 is useful, as it explains more than half of the variation in concentration levels. However, explanatory power is low for specification 1 on income.

Table 3: Estimation results (OLS) and robustness checks reporting coefficients and standard errors for income levels and concentration of income

Variable	DV: individual income (bands)	DV: income concentration (entropy)
Model	(1)	(2)
time (non-art occ.)	-0.183*	-0.007
	0.083	0.017
time (art occ.)	-0.242**	-0.004
	0.083	0.017
non-art occ. dummy	0.067	0.029**
	0.046	0.009
Majors		

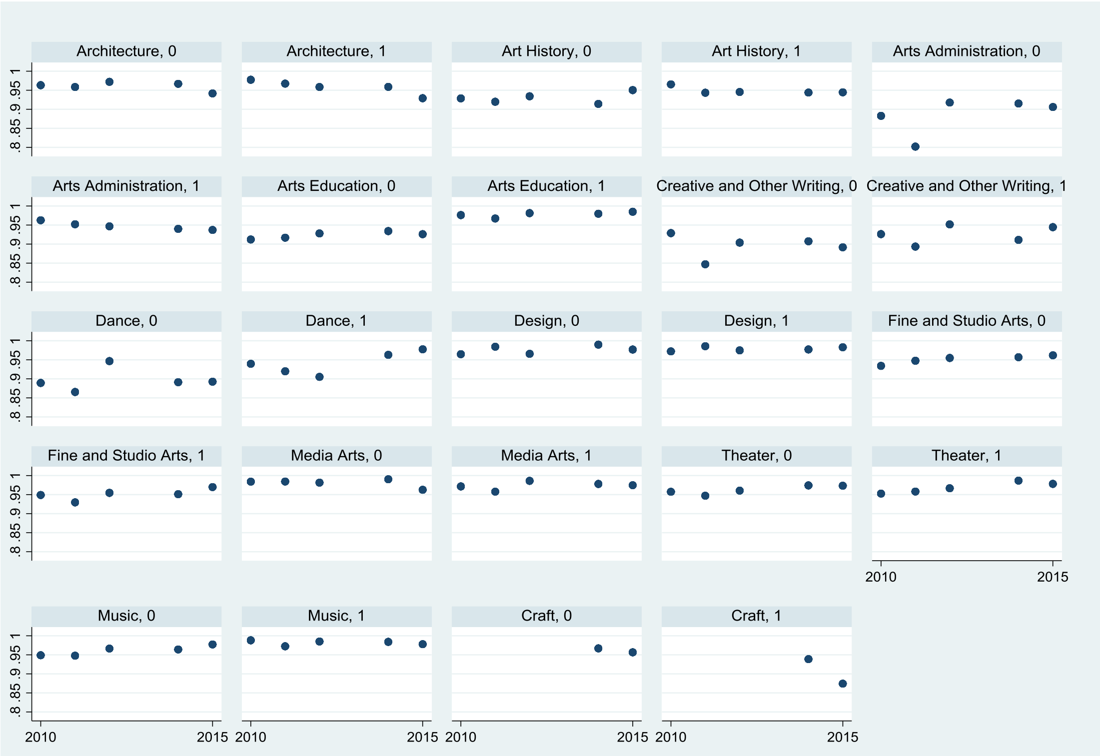
Architecture	2.053***	0.029*
	0.111	0.014
Art History	-0.05	0.009
	0.116	0.014
Arts Administration	-	-0.014
	-	0.014
Arts Education	0.603***	0.021
	0.107	0.014
Creative and Other Writing	-0.490***	-0.019
	0.13	0.014
Dance	-0.483***	-0.011
	0.121	0.014
Design	1.196***	0.048***
	0.105	0.014
Fine and Studio Arts	-0.125	0.021
	0.103	0.014
Media Arts	0.768***	0.047***
	0.106	0.014
Theater	0.322**	0.036*
	0.106	0.014
Music	0.509***	0.041**
	0.104	0.014
Craft	-0.121	-
	0.148	-
real GDP	0.000***	0
	0	0
Const.	-8.214*	0.576
	3.72	0.736
N	92403	114
Adj. R2	0.037	0.527

legend: * p<.05; ** p<.01; *** p<.001
Note: In contrast to the implications from Gini index values, *higher* values of entropy are associated with *lower* levels of income concentration, i.e. a more equal distribution of income.

Source: Based on author calculations and SNAAP data.

As a third step, we descriptively study distributions of income by graduate cohorts, major fields and the type of work occupation. Graph 7 makes a distinction for majors and alumni working within or outside the arts. Thus, it provides early indications on whether concentration is a matter of art labor market or non-art labor market outcomes. To give an example, income distributions of workers with a major in dance are slightly less concentrated when they work outside the arts, and similar applies to those with a major in creative and other writing. So, in turn, it seems to be that dancers or writers cross-subsidizing their work or substituting their occupation tends to explain less concentration of income *across* dancers or writers, if we see distributions becoming more equal over time.

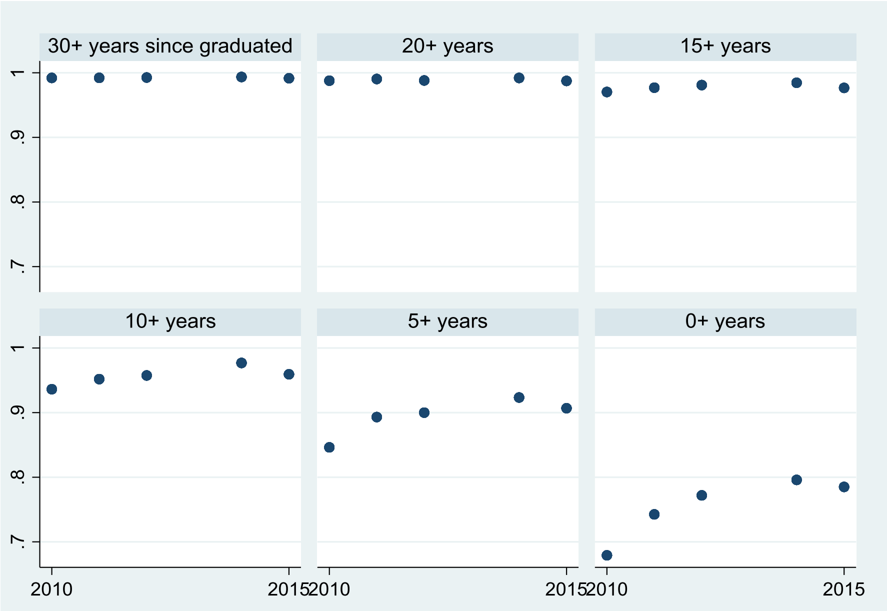
Graph 7: Income concentration ('normalized entropy') by type of occupation (non-art 1, art 0), major field and year.



Source: Based on author calculations and SNAAP data.

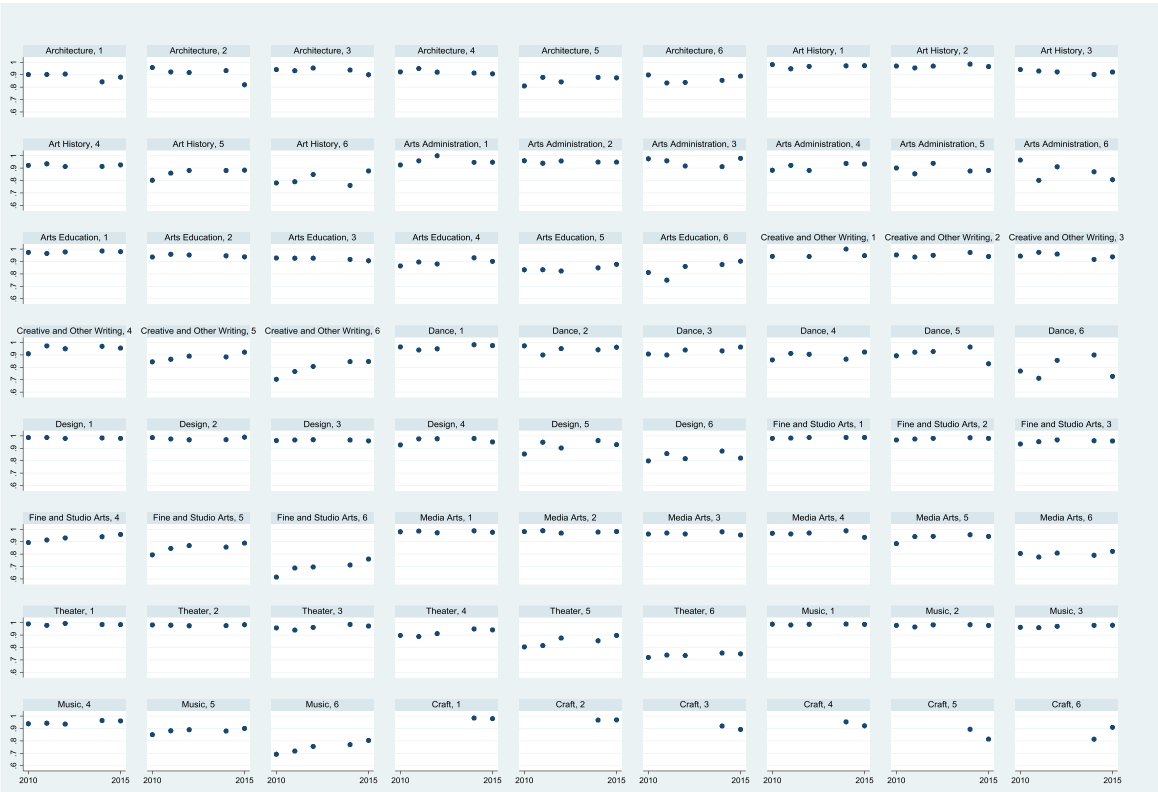
Similarly, graph 8 makes a distinction for majors and alumni from different graduate cohorts. Interestingly, much of the concentration of income is affecting those who more recently graduated from art and music schools and that are only starting artistic careers. This is in line with the literature that argues for steeper age-earnings patterns, with sources of income and multiple job earnings being more dispersed at earlier stages, and new entrants on labor markets being more willing to accept lower offers in return for on-the–job learning opportunities (Menger 1999; Throsby 1999; Rengers 2002). However, this could also be the outcome of a consolidation process where less successful newcomers are dropping out of markets over time. Graph 9 further distinguishes these graduate cohort patterns for income distributions by major fields. Here, it is interesting to note that, over the full observation period, more recent graduate cohorts in certain fields see incomes becoming less polarized and more equally distributed among talents. In several other fields, this is not the case. Still, a trend towards less concentration can be observed, for example, in music, fine and studio arts as well as creative and other writing, all starting from a low basis. However, the SNAAP data does not allow us to disaggregate further and understand whether it is the *specific* cohort's choices or necessities to work and generate income from art *or* in non-art occupations that ultimately changes the shape of their income distributions over time. So, we cannot tell if this trend is based on more new entrants working outside the arts or income distributions changing within the arts.

Graph 8: Income concentration ('normalized entropy') by graduate cohort and year.



Source: Based on author calculations and SNAAP data.

Graph 9: Income concentration ('normalized entropy') by graduate cohort (1 oldest to 6 youngest), major field and year.



Source: Based on author calculations and SNAAP data. Note that graduate cohorts are as follows: (1) 30+ years since graduation, (2) 20+ years, (3) 15+ years, (4) 10+ years, (5) 5+ years, and (6) 0+ years.

Overall, results from the SNAAP data – focused on the United States alone, building on a shorter period from 2010, and using a different identification strategy – do not easily generalize to other countries or main LIS outcomes. The data confirm that creators in art occupations are slightly worse off in comparison to those working in non-art occupations, and it confirms absolute increases in pay for both occupational groups (when not benchmarked on economic growth). Arguably, in both groups, workers rely to a certain degree on the same set of creative, non-routine skills that – according to skill biased technological change theories – will enable them to demand higher pay over time, corroborating previous LIS results. Notably, we also do not find any systematic trend in the concentration of income across major fields and over time which differs slightly from the overall U.S. trend observed in the descriptive LIS data, i.e. (self-employed) creators' incomes becoming slightly more dispersed over time.

III: KSK data

In this section, the analysis builds on unique data from public social insurance records ('Kuenstlersozialversicherungskasse' or KSK), a national insurance scheme exclusively targeting self-employed creators located in Germany. Participation in the scheme requires creators to earn and report on their income from artistic self-employment. Notably, the data can be considered as representative of the total population of self-employed creators based in Germany. In this way, it is comparable to the LIS self-employment data for Germany with only few exceptions[25] and allows us to study patterns of entry and supply over time, as well as the identification of time trends by artistic category.

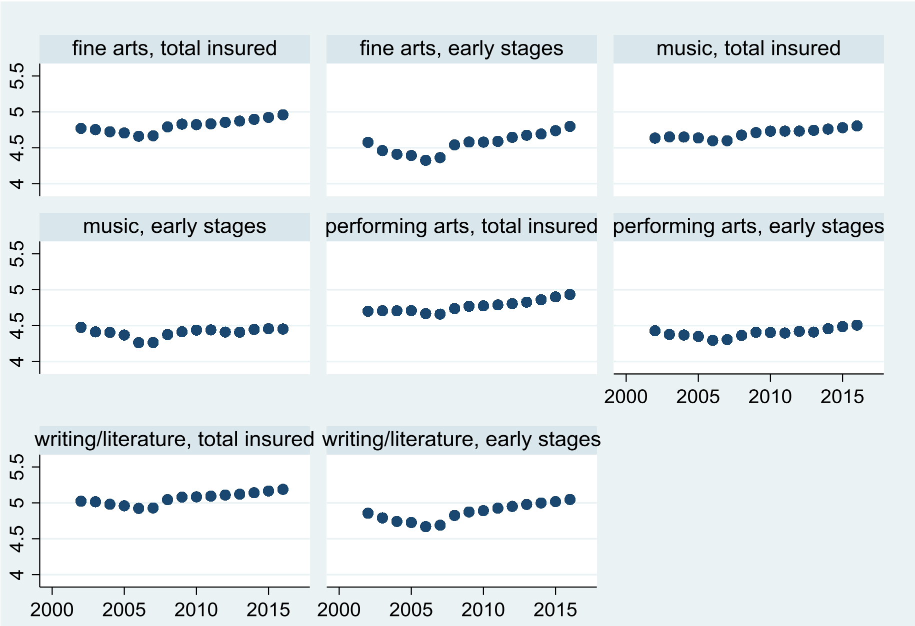
Creators self-select into artistic categories with their initial application to the scheme, i.e. fine arts, performing arts, music or writing/literature. The KSK data covers income/net revenue averages (mean) in the total insured population by gender, German 'Laender', year, artistic category and age group, for the observation period from 2002 to 2017. Similar information is available for a subset of KSK insured creators at early stages of their career. The KSK defines 'early stages' as the first three years after starting artistic self-employment. This is a useful feature of the data because it allows us to identify the entry of creators to markets rather than having to rely on 'net' supply figures in equilibrium only, i.e. it remains unknown how many creators enter and exit markets at a given point in time. However, several caveats apply to the data. For example, note that average values, i.e. the level of the analysis, do not allow for the teasing out of changes in income distributions themselves. Accordingly, an analysis of income concentration is not feasible. Moreover, the KSK data does not provide any information on cross-subsidizing or substitution of art work, such employment in non-art occupations or the contribution of spouses' income on household level. In addition, records do not cover income sources from work arrangements in the arts other than self-employment.

As a first step, we descriptively study the changes in average income from self-employed art work and approximate the changes in entry and supply of artistic labor over time via the number of persons insured under the KSK scheme at a given point in time.

Graph 10 distinguishes population-weighted, average income levels in real terms (reference year is 2010) by career stages and by artistic category, log-transforming values on the y-axis. Across artistic categories, average income is substantially lower for early stage creators than for those in the total population of creators insured by KSK. However, in both samples, nominal income – more precisely, net revenues from self-employment reported to tax authorities – is on the rise. To give an example, while in 2002 the 'average' musician in the total KSK population (early stage musicians) earned 9,310 Euros (8,265) from self-employment in the arts, his or her average nominal income rose to 13,675 Euros (9,611) in 2017.

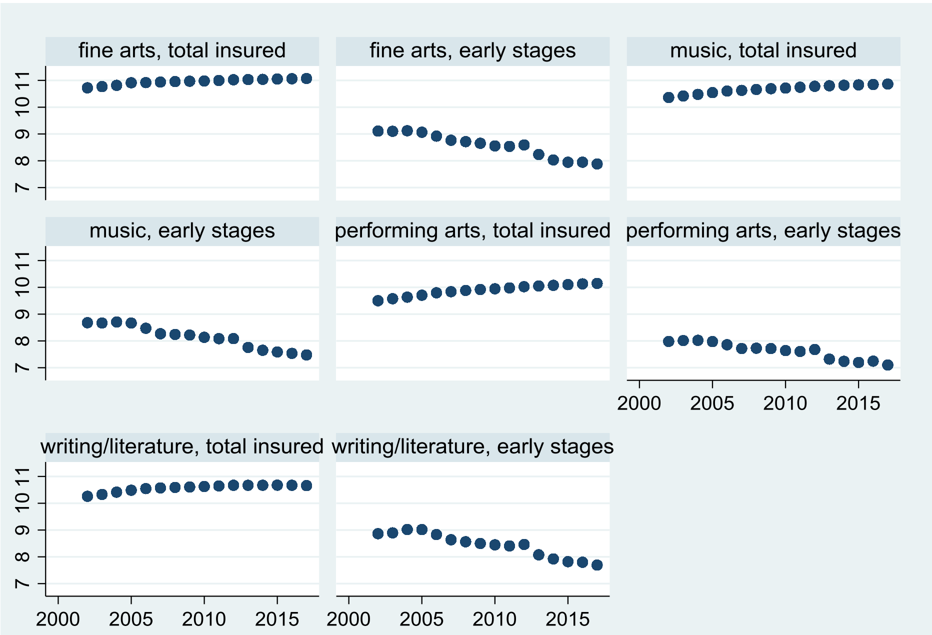
In addition, graph 11 distinguishes log-transformed, annual stocks/net supplies of insured persons under the KSK scheme by career stages and by artistic category. Notably, the number of new entrants to markets, i.e. creators at early career stages, is decreasing over time. At the same time, the total population of KSK insured and, thus, overall supply of creative labor is weakly increasing. For example, the absolute number of self-employed musicians located in Germany and recorded in the total insurance data (early stage musicians) stood at 31,640 (5,889) in 2002, while in 2017 the data listed 52,226 (1,767). Economically speaking, changes in the total insured population might suggest that rising nominal income induces additional supply of creative labor. However, as supply and income levels are simultaneously determined, it may equally be the case that the decrease of new professionals entering markets causes higher earning at early career stages due to lowering competitive pressures.

Graph 10: Real income of KSK insured by career stage, artistic category and year, log-transformed, population-weighted average values.



Source: Based on author calculations and KSK data.

Graph 11: Total number of persons insured under the KSK scheme by career stage, artistic category and year, log-transformed values.



Source: Based on author calculations and KSK data.

As a second step, we econometrically investigate time trends in real income levels (with base year 2010, specifications 1 and 3) and approximate trends in the net supply and entry of self-employed, creative labor (2 and 4). Again, we deploy basic OLS models in all specifications and run separate regressions for each dependent variable and for each sample, total insured (1 and 2) and early stages specifications (3 and 4). All specifications presented in table X include art-category and age-cohort fixed-effect. In addition, we insert Laender level nominal GDP.

As concerns real income levels in Germany, overall we can confirm a positive time trend in any artistic category for the observation period (1), without adjusting for economic cycle effects in a multivariate setting (please refer to table 4 and table A.9 in the annex). However, income trends do not persist across categories when we limit the data to early stage creators only (3), but are insignificant in the performing arts and music. Notably, this discharges our preliminary assessment of the data based on the descriptive analysis, at least partially.

As concerns the overall supply of creative labor, we identify positive time trends in each of the four artistic categories in the total insured population (2). In contrast, we find support for significant negative trends as regards new entry of creators (4), in line with expectations from the previous analysis step and the visualization of the data. Accordingly, it seems that fewer creators enter than exit markets over time, partially because creators are actively pursuing careers for longer periods of time.[26]

Moreover, fixed effects results confirm that there are substantial differences between artistic categories as regards their specific income as well as supply levels. For example, average income levels are generally higher in writing/literature (reference category) in comparison to other categories among those insured. Similarly, fewer people enter and work in the performing arts at the outset. Moreover, we find very preliminary evidence on an income gap in Germany at the burden of female creators among the insured. However, we also find that a higher proportion among new entrants/early stagers are women, suggesting that creative supply might become more diverse in long term.

Table 4: Estimation results (OLS) and robustness checks reporting coefficients and standard errors for real income levels and total number of KSK insured and by career stage.

sample	**total insured**		**early stages**	
variable	**DV: log income**	**DV: log number insured**	**DV: log income**	**DV: log number insured**
model	(1)	(2)	(3)	(4)
time (fine arts)	0.015***	0.038***	0.017***	-0.046***
	0.001	0.007	0.003	0.008
time (performing arts)	0.007***	0.060***	0.001	-0.027***
	0.001	0.007	0.003	0.008
time (music)	0.005***	0.059***	0	-0.052***
	0.001	0.007	0.003	0.008
time (writing)	0.013***	0.044***	0.017***	-0.041***
	0.001	0.007	0.003	0.008
art category				
fine arts	-0.321***	0.559***	-0.380***	0.084
	0.015	0.082	0.031	0.084
performing arts	-0.225***	-0.659***	-0.297***	-0.957***
	0.015	0.082	0.032	0.086
music	-0.277***	0.176*	-0.305***	-0.089
	0.015	0.082	0.031	0.084
writing	reference category			

gender (male)	0.240***	0.211***	0.198***	-0.175***
	0.004	0.023	0.009	0.024
age: below 30	-0.279***	-0.783***	0.022	2.265***
	0.007	0.037	0.017	0.047
30-40	-0.131***	1.208***	0.051**	3.133***
	0.007	0.036	0.017	0.047
40-50	0.013	1.567***	0.081***	2.187***
	0.007	0.036	0.017	0.047
50-60	0.056***	1.118***	0.068***	1.254***
	0.007	0.036	0.018	0.048
above 60	reference category			
nom. GDP, regional	0.009*	-0.038*	0.012	-0.083***
	0.004	0.019	0.007	0.02
const.	4.557***	4.243***	4.188***	3.231***
	0.086	0.455	0.177	0.479
N	10166	10167	8545	8554
adj. R2	0.518	0.413	0.232	0.436
legend: * p<.05; ** p<.01; *** p<.001				

Source: Based on author calculations and KSK data. Note: KSK defines ‘early stages’ as the first three years after starting artistic self-employment.

Overall, results from the KSK data – as they focus on insured creators located in Germany, are limited to very specific artistic categories, and use yet another identification strategy – do not easily generalize to other countries or main LIS outcomes.

Interestingly, the data does not corroborate the idea of lower-cost entry in the digital era, but shows the opposite effect: a decline in the number of new entrants over time and in all artistic categories (4), while simultaneously net supply increases (i.e. the total insured population is growing) (2). This former outcome is even more unexpected as new entrants might also be first adopters of new, more cost-efficient digital technologies. Alternatively, digital technologies might not be lowering generation costs as predicted in the previous literature.

Income time trends suggest that not all early stagers – different to the rest of the insured population – benefit from the overall positive wage effects we find, possibly associated with skill biased technological changes.[27] There might be other factors that explain why some early stage income is not improving that are unobserved in the current analysis frame. However, based on the above, we seem to be able to rule out one of the potential reasons, namely a decline in income due to higher entry, as competitive wage pressures in this group (4) should decrease over time.

In general, from the KSK analysis it follows that a distinction of career stages is very useful as each group might experience different time trends in entry/supply and income levels. Moreover, it turns out that effects can be specific to artistic categories. Finally, new entrants might be among those creators most affected by technological change. This group faces lower income (and, more severely, lowering income over time in some categories relative to the total population trend) and also experiences less entry of new talent over time. These issues and what causally drives our observations here will, of course, require more empirical inquiry in the future.

DISCUSSION AND LIMITATIONS

This study is subject to certain limitations and there is a need to conduct further empirical research on some of these issues.

First, our approach to income trends is purely observational. We do not implement a causal research design and cannot identify the drivers causing trends to change over time. In particular, even though the research might well approximate 'compound' effects of digital change on income and income distribution trends, it does not allow to distinguish positive from negative effects. For example, digital technologies might be lowering production or distribution costs. At the same time, online consumption might differ from previous consumption patterns offline, favoring some artists over others (for example, Datta et al 2018). And, competition levels and stakeholders' bargaining positions in value chains might also be changing and, ultimately, affect the incentives to create and distribute new content, once there is 'disintermediation' or entry of new stakeholders to markets (Hviid et al 2017a, 2017b). Each of these aspects of digital change has its own implications for the distribution of income and level changes over time and needs to be confirmed by further empirical research. However, it is interesting that there are no substantial differences in the way income is changing in the various sectors of the creative economy, at least in the U.S. and in Germany. Artistic disciplines and fields of study such as music or creative writing that, arguably, seem more 'exposed' to digital technologies and distribution changes (when compared to performing or visual arts) do not show systematically different time trends in the analysis of the data: For example, in Germany, positive income trends can be observed in each of the artistic disciplines among those insured. In the U.S., the distribution of income among art graduates is not becoming more unequal in sectors where there is exposure to digital change.

Second, the data we deploy are cross-sectional and not longitudinal in nature at the level of individual creator, meaning we cannot monitor individuals and their activities over time. More specifically, we cannot observe artists' income situation over the course of careers and we cannot assess whether or not the digital environment has an impact on their supply of art work choices, as well as entry and exit of artists in these markets. Similarly, the data does not allow us to combine and match information on income or revenue positions with information on artist-level production of new works over time and sales/economic 'uses' data based on how much works are in demand. Moreover, we are unable to identify and assess the specific contribution of 'copyright-generated' streams of income, for example, income from royalty payments. In principle, it is possible that the time trends in total income we identify differ from the trends in copyright-generated streams.

Third, research in this study does not link up to specific legal rules in the copyright system and does not assess 'economic performance' or efficacy of rules. Ideally, we would want to study those copyright rules that are closely tied to the main concern of our study, the income and bargaining positions of creators: so-called 'statuary provisions' which aim to regulate the contracting that typically involves original creators (and their work) and another party or intermediary engaged in the exploitation and distribution of the former's work. For example, provisions might limit the scope of contracts as regards the parties' ability to contract on future or unknown uses of works. These provisions often aim to preserve the interest of the party with weaker bargaining power, typically the original creator who attempts to transfer or license works of unknown value in a contract (Towse 2018). Preliminary research on the effects of such provisions on artistic income observes an income premium in certain artistic occupations (Guibault et al 2015, 2016).[28] However, on the basis of the data we deploy in this study it seemed impossible to further investigate in this direction.

Finally, the rise of online contract labor markets in certain creative professions can be yet another determinant of changing income. This is an area of research that clearly deserves more empirical investigation in the future. So far, we only very briefly discuss in the section reviewing the previous literature how online platforms can change creators' access to work opportunities and, ultimately, how they may alter the way income is distributed. Based on the existing evidence, however, one can expect online work arrangements to reinforce 'repeat hiring' patterns in talent discovery and winner-takes-all mechanisms already present in these markets, partially because online screening and reviewing mechanisms introduce new information frictions (Bessen 2016; Agrawal et al 2016).

SUMMARY AND CONCLUSIONS

Wage trends for creative workers outperform those in other occupations in the digital age. Research based on the Luxembourg Income Study (LIS) database covering several countries around the world and national microdata since the turn of the century lends support to the wage-implications from skill-biased technological change theories (for example, Acemoglu and Autor 2011). It seems non-routine skills associated with creative occupations are better paid in the digital age as income trends over time systematically differ from trends observed in the overall population. These results are also in line with general income trends discussed in research by Piketty et al (2018) and others, suggesting that real wages have been stagnating in the past and have been outpaced by economic growth. Results continue to hold using alternative estimation approaches and data sources.[29]

From a policy perspective, these results do not lend support to the idea that creators' income situation has systematically worsened with the rise of the internet and its intermediaries, as argued by some commentators in 'value gap' discussions. The income changes creators experience over time are not aligned with general trends in the total population: we see creators losing less or even gaining a better income position in relative terms.[30]

We find ambiguous evidence across our data sources as regards an 'income penalty' for creators as evidenced in much of the older literature, i.e. creators' having lower income levels than average income in other occupations. Our results in this respect depend on control group choices and, in general, measuring these income differences is not a main concern of the study. At the same time, the EVS analysis offers preliminary evidence of a 'satisfaction premium' for creators, i.e. average satisfaction levels among creators being substantially higher than in other occupations. Artists have different criteria and conceptualizations when it comes to what is considered a 'good' job and income, as they may derive value and satisfaction from their work in a variety of ways aside from income and commercial success.

Artists do not have uniform motivations to create. Policy deliberations should thus take into account non-monetary sources of artists' motivation and carefully build incentive schemes targeting overall psychic income, rather than focusing on income issues alone. For example, changes in legal and other mechanisms can affect peer recognition and ease of attribution of works, which ultimately influence creators' job satisfaction and further creativity.[31] Income-focused reforms might effectively lead to missing policy goals.[32]

Relative to the total workforce, the LIS data proposes that the net supply of creative occupations labor has increased over time in most countries included in the sample. This might suggest that content generation costs are decreasing in the digital age as argued by Waldfogel and several others (Waldfogel 2012; Aguiar and Waldfogel 2016; Waldfogel and Reimers 2015), lowering market entry costs for creators. Complementary to this, we might also be observing macro level trends where parts of the workforce are transitioning from high-productivity manufacturing to low-productivity services jobs (Baumol and Bowen 1966). Unfortunately, the LIS data does not allow us to distinguish these effects, nor causally address them in an adequate research design.

Interestingly, analysis of the KSK data reveals that the number of new creators entering artists' labor markets in Germany (and seeking insurance according to the KSK records) is decreasing over time, in contrast to the net supply numbers that do not distinguish the in- and out-flows of artists. This trend does not hold for the total insured population, which slightly increases, partly because creators tend to work longer periods in their lives. Even though we cannot fully rule out changing incentives to seek insurance over time, the decrease in numbers is somewhat surprising: arguably, new entrants should also be among the early adopters of these (supposedly) more cost-efficient digital technologies.

Finally, we study the distribution of income on the basis of the LIS data. However, similar to other comparative studies on the evolution of income distribution (Nolan et al 2016, 2018), our results are highly country-specific. One of the reasons is that broader macro factors and labor market institutions, as well as factors specific to creators' income, differ from one country to the other. Accordingly, strong statements about the distributional effects associated with the 'value gap' are not warranted as country context matters a great deal. However, the LIS analysis yields other interesting results. One is that income dispersion is more pronounced among self-employed creators than those that are regularly employed. And, more interesting, income in creative occupations is less concentrated than in most other occupations. Using another data source, analysis of U.S. art and music schools graduates' professional careers suggests that post-graduation income is more equally distributed when working in non-art occupations than in art ones. In turn, this means any cross-subsidizing of these (trained) artists may also affect their overall exposure to income inequality. In many instances, artists cross-subsidize or back income from working in the arts with additional income from non-art work, effectively being multiple job holders. Also, more recent graduate cohorts from U.S. art and music schools seem to be more exposed to this effect.

A key takeaway from the KSK and SNAAP analysis is that more recent graduates or early stage creators might be among those most affected by technological changes. In general, this group exhibits lower income levels and higher income inequalities. In addition, there is preliminary evidence of a decline of market entry over the last two decades.

From a policy perspective, a reduced inflow of new talent to markets has several welfare implications and suggests that the 'one-size-fits-all' approach across career stages might be insufficient.

First, to the extent that 'lost' creators find jobs elsewhere in the economy, the labor market effects may be quite benign. It seems more problematic and welfare-decreasing when creators exit creative labor at their later career stages, when they are less likely to find alternative employment.

Second, to the extent that the dominance of well-established and 'bourgeoisie' artists increases, content production systems might have lost some of their ability to host and incentivize the entry of autonomous avant-garde artists (Senftleben 2017). For example, contemporary Western pop music might become more homogenous as an outcome (Serra et al 2012; Askin and Mauskapf 2017). These creators typically build truly new movements and discover new artistic styles, with no or few market prospects, and often oppose the direction of the more mainstream production. Property right systems (including copyright) have little to offer in such a scenario, as they are based on market signals. Ultimately, this also calls into question if such artists are essential for enabling the system to 'recreate' on a constant basis, and how many new works in the arts rely on the existence and inspiration of predecessors, or are 'genuinely' new ones.[33] Economic problems around these dynamic issues include the efficient allocation of incentives and resources over time, hold up problems when there is more reuse downstream, as well as finding cost-efficient ways to achieve overarching policy goals.[34] In any case, this area of research also deserves more empirical investigation in the future.

REFERENCES

Abbing, H. (2004). Why Are Artists Poor?: The Exceptional Economy of the Arts. 1st Edition. Amsterdam University Press: Amsterdam.

Acemoglu, D. (2002). Technology and the Labor Market. *Journal of Economic Literature, 40*, 7-72.

Acemoglu, D., & Autor, D.H. (2011). Skills, tasks and technologies: implications for employment and earnings. In Ashenfelter, O., Card, D. (eds.): *Handbook of Labor Economics*, vol. 4B, 1043–1171. North Holland: Amsterdam.

Adler, M. (2006). Stardom and Talent, In Ginsburgh, V. A., & Thorsby, D. (eds.), *Handbook of the economics of arts and culture*. North Holland: Amsterdam.

Agrawal, A., Horton, J., Lacetera, N., & Lyons, E. (2015). Digitization and the Contract Labor Market: A Research Agenda. In Goldfarb, A., Greenstein, S., & Tucker, C. (eds.): *Economic Analysis of the Digital Economy.* University of Chicago Press: Chicago.

Aguiar, L., & Waldfogel, J. (2017). Quality Predictability and the Welfare Benefits from New Products: Evidence from the Digitization of Recorded Music. *Journal of Political Economy, 126*(2), 492-524.

Alper, N. O., & Wassall, G. H. (2006). Artists' careers and their labor markets. In Ginsburgh, V. A., & Thorsby, D. (eds.), *Handbook of the economics of arts and culture*. North Holland: Amsterdam.

Amabile, T. (1998). How to kill creativity. *Harvard Business Review, 76*, 76– 87.

Anderson, C. (2006). The Long Tail: How Endless Choice Is Creating Unlimited Demand. Random House: London.

Araujo, R. M. (2013). 99designs: An Analysis of Creative Competition in Crowdsourced Design. In Proceedings of the First AAAI Conference on Human Computation and Crowdsourcing: 17–24, Palm Spring, CA, November 7–9, 2013.

Arrow, K. (1972). Gifts and Exchanges. *Philosophy and Public Affairs, 1*(2), 343-62.

Askin, N., & Mauskapf, M. (2017). What Makes Popular Culture Popular? Product Features and Optimal Differentiation in Music. *American Sociological Review*, 82(5), 910 – 944.

Åstebro, T., Chen, J., & Thompson, P. (2011). Stars and misfits: self-employment and labor market frictions. *Management Science*, *57*(11), 1999–2017.

Atkinson, A., Piketty, T., & Saez, E. (2011). Top Incomes in the Long Run of History. *Journal of Economic Literature*, *49*(1), 3-71.

Attladotir, K., Kretschmer, M., & Towse. R. (2014). Artists, authors' rights and copyrights. In: Towse, R., & Handke, C. (eds.), *Handbook on the Digital Creative Economy*, 274-83. Edward Elgar: Cheltenham.

Autor, D. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives, 29*(3), 3-30.

Autor, D., Levy, F., & Murnane, R. (2003). The skill content of recent technological change: an empirical exploration. *Quarterly Journal of Economics, 116*(4), 1279–1333.

Baer, M., & Oldham, G. (2006). The curvilinear relation between experienced creative time pressure and creativity. *Journal of Applied Psychology, 91*(4), 963–970.

Bakhshi, H., Freeman, A., & Higgs, P. (2012). A dynamic mapping of the UK's creative industries. NESTA: London.

Bakhshi, H., Frey, C., & Osborne, M. (2015). Creativity vs Robots. NESTA: London.

Bakhshi, H., Davies, J., Freeman, A., & Higgs, P. (2015). The geography of the UK's creative and high–tech economies. NESTA, London.

Bar-Isaac, H., Guillermo C., & Cuñat, V. (2012). Information Gathering Externalities for a Multi-Attribute Good. *The Journal of Industrial Economics, 60*(1), 162–185.

Baumol, W., & Bowen, W. (1966). Performing Arts, The Economic Dilemma: a study of problems common to theater, opera, music, and dance. Twentieth Century Fund: New York.

Bechtold, S., & Engel, C. (2017). The Valuation of Moral Rights: A Field Experiment. Discussion Paper Series of the Max Planck Institute for Research on Collective Goods 2017_04. Max Planck Institute for Research on Collective Goods: Bonn.

Buccafusco, C., Bechtold, S., & Sprigman, C. (2017). The Nature of Sequential Innovation. *Wm. & Mary Law Review*, 59(1).

Bénabou, R., & Tirole, J. (2003). Intrinsic and extrinsic motivation. *Review of Economic Studies, 70*, 489–520.

Bessen, J. (2016). How Computer Automation Affects Occupations: Technology, Jobs, and Skills. Boston Univ. School of Law, Law and Economics Research Paper No. 15-49. Available at SSRN: https://ssrn.com/abstract=2690435 or http://dx.doi.org/10.2139/ssrn.2690435.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, 100(5), 992–1026.

Bille, T., & Jensen, S. (2018). Artistic education matters: survival in the arts occupations. *Journal of Cultural Economics, 42*(1), 23–43.

Bille, T., & Lorenzen, M. (2008). Den danske oplevelsesøkonomi – afgrænsning, økonomisk betydning og vækstmuligheder. Forlaget Samfundslitteratur: Copenhagen.

Bille, T., Fjællegaard, C., Frey, B., & Steiner, L. (2013). Happiness in the arts—International evidence on artists' job satisfaction. *Economics Letters, 121*(1), 15-18.

Blinder, A. (2007). How Many U.S. Jobs Might Be Offshorable? Centre for European Policy Studies working paper no. 142. Princeton University: Princeton, NJ.

Block, J., Sandner, P., & Spiegel, F. (2015). How do risk attitudes differ within the group of entrepreneurs? The role of motivation and procedural utility. *Journal of Small Business Management, 53*(1), 183-206.

BLS -Bureau of Labor Statistics (2017). Measuring the 'Gig' economy, presentation held by Michael W. Horrigan, October 4, 2017, Expert Group Meeting Measuring the Quality of Employment, https://www.unece.org/fileadmin/DAM/stats/documents/ece/ces/ge.12/2017/mtg1/Session_4_1-_USA-BLS_-_US_Contingent_workers_May_2017.pdf

Bourdieu P. (1992). Les regles de I'art. Seuil: Paris.

Brynjolfsson, E., Hu, Y., & Simester, D. (2011). Goodbye Pareto Principle, Hello Long Tail: The Effect of Search Costs on the Concentration of Product Sales. *Management Science*, *57*(8), 1373-1386.

Buccafusco, C., & Sprigman, C. (2011). The Creativity Effect. *University of Chicago Law Review, 78*(1).

Casacuberta, C., & Gandelman, N. (2012). Multiple Job Holding: The Artist's Labor Supply Approach. *Applied Economics, 44*(3), 323-337.

Caserta, M., & Cuccia, T. (2001). The Supply of Arts Labour: Towards a Dynamic Approach. *Journal of Cultural Economics, 25*(3), 185–201.

Caves, R. (2000). Creative industries: contracts between art and commerce. Harvard University Press: Harvard.

Cetruloa, A., Cirillo, V., & Guarasciob, D. (2018). Weaker jobs, weaker innovation. Exploring the temporary employment-product innovation nexus. ISI Growth working paper.

Chartered Institute of Personnel and Development - CIPD (2017). Survey Report, To gig or not to gig? Stories from the modern economy. London.

Cowen, T., & Tabarrok, A. (2000). An economic theory of avant-garde and popular art, or high and low culture. *Southern Economic Journal, 67*(2), 232–253.

Crane, D. (1987). The Transformation of the Avant-Garde. University of Chicago Press: Chicago.

Datta, H., Knox, G., & Bronnenberg, B. (2018), Changing Their Tune: How Consumers' Adoption of Online Streaming Affects Music Consumption and Discovery. *Marketing Science,37*(1), 1-175.

Debeauvais, R., Menger, P., Rannou, J., Vari, S., & Laplante, B. (1997). Le spectacle vivant. Paris: La Documentation Franqaise, Collection Contrats d'Etudes Prospectives.

Dettling, L. (2014). Broadband in the Labor Market: The Impact of Residential High Speed Internet on Married Women's Labor Force Participation. *ILR Review, 70*(2), 451–482.

Dreze J. (1987). Human capital and risk-bearing. In Essays on Economic Decisions under Uncertainty. Cambridge University Press: Cambridge, MA.

Elstad, J. (1997). Collective Reproduction through Individual Efforts: The Location of Norwegian Artists in the Income Hierarchy. *International Journal of Cultural Policy, 3*(2), 267-288.

Facundo, A., Atkinson, A.B., Piketty, T., & Saez E. (2013). The Top 1 Percent in International and Historical Perspective. *Journal of Economic Perspectives, 27*(3), 3-20.

Fehr, E.; & Schmidt, K. (2006). The Economics of Fairness, Reciprocity and Altruism - Experimental Evidence and New Theories. In Kolm, S. and Ythier, Jean Mercier, (Eds.), *Handbook of the Economics of Giving, Altruism and Reciprocity*, vol. 1, 615-691. Amsterdam: Elsevier.

Filer, R.K.. (1986). The "Starving artist"-Myth or reality? Earnings of artists in the United States. *Journal of Political Economy, 96*, 56-75.

Filer, R. K. (1990). Arts and academe: the effects of education on earnings of artists. *Journal of Cultural Economics, 2*, 15-38.

Forman, C., Goldfarb, A., & Greenstein, S. (2012). The Internet and Local Wages: A Puzzle. *American Economic Review, 102*(1), 556-75.

Fosnacht, K., Sarraf, S., Howe, E., & Peck, L. K. (2017). How important are high response rates for college surveys? *The Review of Higher Education, 40*(2), 245-265.

Freelancers Union (2017). Freelancing in America study. Joint Research with Upwork.

Frey, B. S., & Pommerehne, W. (1989). Muses and Markets. Blackwell: Cambridge.

Frey, B. S., & Jegen, R. (2001). Motivation crowding theory: A survey of empiricial evidence. *Journal of Economic Suvreys, 15*(5), 589-611.

Guibault, L., Salamanca, O., & van Gompel, S. (2015). Remuneration of authors and performers for the use of their works and the fixations of their performances. Study commissioned by the European Commission and conducted by Europe Economics.

Guibault, L., & Salamanca, O. (2016). Remuneration of authors of books and scientific journals, translators, journalists and visual artists for the use of their works. Study commissioned by the European Commission and conducted by Europe Economics.

Halvarsson, D., Korpi, M., & Wennberg, K. (2018). Entrepreneurship and income inequality, *Journal of Economic Behavior & Organization, 145*, 275-293.

Handke, C., Girard, Y., & Mattes, A. (2015), Fördert das Urheberrecht Innovation? Eine empirische Untersuchung, Studien zum deutschen Innovationssystem, Nr. 16-2015, Expertenkommission Forschung und Innovation: Berlin.

Handke, C., Stepan, P., & Towse, R. (2016), Cultural Economics and the Internet. In Bauer, J. & Latzer, M. (eds.). *Handbook on the Economics of the Internet*. Edward Elgar Publishing.

Hansen, K.T. (2004). Helping or hindering? Controversies around the international second-hand clothing trade. *Anthropology Today, 20*(4), 3–9.

Hargittai, E., & Walejko, G. (2008). The participation divide: Content creation and sharing in the digital age. Information, *Communication & Society, 11*(2), 239–256.

Hesmondhalgh, D. (1996). Flexibility, post- Fordism and the music industry. *Media, Culture, Society, 18*, 469-88.

Howe, J. (2006). The rise of crowdsourcing. *Wired magazine 14*(6),1–4.

Huang, Y., Singh, P., & Mukhopadhyay, T. (2013). How to Design Crowdsourcing Contest: A Structural Empirical Analysis. Proceedings of the Conference on Information Systems and Technology.

Hviid, M., Jacques, S., & Izquierdo Sanchez, S. (2017a). From publishers to self-publishing: The disruptive effects of digitalisation on the book industry. Zenodo.

Hviid, M. & Izquierdo Sanchez, S., & Jacques, S. (2017b). Digitalisation and intermediaries in the music industry. MPRA Paper 79018, University Library of Munich, Germany.

International Federation of the Phonographic Industry - IFPI (2010). Investing in Music: How Music Companies Discover, Develop, and Promote Talent.

Kässi, O., & Lehdonvirta, V. (2016). Online Labour Index: Measuring the Online Gig Economy for Policy and Research. Paper presented at Internet, Politics & Policy 2016, Oxford, UK, 22-23 September. http://ilabour.oii.ox.ac.uk/online-labour-index/

Katz, L., & Krueger, A. (2016). The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015. Working Papers 603, Princeton University, Department of Economics, Industrial Relations Section.

Kennedy, J., Tepper, S., & Lambert, A. (2010). An analysis of mode effects in three survey modes in the Strategic National Arts Alumni Project. Paper presented at the 2nd International Workshop on Internet Survey Methods, Daejeon, South Korea.

Kerr, S., Kerr, W., & Xu, T. (2017). Personality Traits of Entrepreneurs: A Review of Recent Literature, NBER Working Papers 24097, National Bureau of Economic Research, Inc.

Knight, F. (1921). Risk, Uncertainty, and Profit. Houghton Mifflin Co.: Boston, MA.

Kretschmer, M., Derclaye, E., Favale, M., & Watt, R. (2010). A Review commissioned by the UK Strategic Advisory Board for Intellectual Property Policy (SABIP).

Kretschmer, M., Bently, L., Singh, S., & Cooper, E. (2011). Copyright Contracts and Earnings of Visual Creators: A Survey of 5,800 British Designers, Fine Artists, Illustrators and Photographers.

Lambert, A. D., & Miller, A. L. (2014). Lower response rates on alumni surveys might not mean lower response representativeness. *Educational Research Quarterly, 37*(3), 38.

Liebowitz, S., & Zentner, A. (2018). Motivations to Create. Working paper, preliminary version.

Lucchese, M., & Bogliacino, F. (2011). Endogenous Skill Biased Technical Change: Testing for Demand Pull Effect, LIS Working papers 574, LIS Cross-National Data Center, Luxembourg.

Manyika, J., Lund, S., Bughin, J., Robinson, K., Mischke, J., & Mahajan, D. (2016). Independent Work: Choice, Necessity, and the Gig Economy. McKinsey Global Institute: San Francisco.

Menger, P.M. (1999). Artistic Labor Markets and Careers. *Annual Review of Sociology, 25,* 541-574.

Miller, R. (1984). Job matching and occupational choice. *Journal of Political Economy, 92*, 1086-120.

Miller, A., & Cuntz, A. (2018). Unpacking Predictors of Income and Income Satisfaction for Artists. Economic Research Working Paper Series, no. 50. Geneva: World Intellectual Property Organization.

Mollick, E., & Nanda, R. (2016). Wisdom or Madness? Comparing Crowds with Expert Evaluation in Funding the Arts. *Management Science, 62*(6), 1533-1553.

Moulin, R. (1992). L'artiste, l'institution et le marche. Flammarion: Paris.

Nathan, M., Pratt, A., & Rincon–Aznar, A. (2015). Creative economy employment in the EU and the UK: A comparative analysis. NESTA: London.

Nathan, M., Kemeny, T., Pratt, A., & Spencer, G. (2016). Creative economy employment in the US, Canada and the UK: A comparative analysis. NESTA: London.

Neckermann, S., Cueni, R., & Frey, B. S. (2014). Awards at work, *Labour Economics, 31,* 205-217.

Nolan, B., Roser, M., & Thewissen, M. (2016). Stagnating median incomes despite economic growth: Explaining the divergence in 27 OECD countries. VoxEU.org, 27 August.

Nolan, B., Roser, M., & Thewissen, M. (2018). GDP Per Capita Versus Median Household Income: What Gives Rise to the Divergence Over Time and How Does This Vary Across OECD Countries? Review of Income and Wealth.

O'Brien, J., Feist, A. (1995). Employment in the Arts and Cultural Industries: An Analysis of the 1991 Census. Arts Council England: London.

OECD (1994): OECD jobs study: facts, analysis, strategy.

Pallais, A. (2012). Inefficient Hiring in Entry-Level Labor Markets. *The American Economic Review, 104*(11), 3565-3599.

Paul, A., & Kleingartner, A. (1994). Flexible production and the transformation of industrial relations in the motion picture and television industry. *Industrial Labor Relations Review, 4*, 662-78.

Peacock A., & Weir, R. (1975). The Composer in the Market Place. Faber: London.

Peltier, S., & Moreau, F. (2012). Internet and the “Long Tail versus superstar effect” debate: Evidence from the French book market. *Applied Economics Letters, 19*(8), 711–715.

Piketty, T. (2014). Capital in the Twenty-First Century. The Belknap Press of Harvard University Press: Harvard.

Piketty, T., Saez, E., & Zucman, G. (2018). Distributional National Accounts: Methods and Estimates for the United States. *Quarterly Journal of Economics, 133*(2): 553-609.

Poort, J., Akker, I., Rutten, P., & Weda, J. (2013). Perspectives of creators and performers on the digital era. *New Media & Society, 17*(5), 666–690.

Popović, M. & Ratković, K. (2017). Oversupply of Labor and Other Peculiarities of Arts Labor Market. *Theoretical And Practical Research In The Economic Fields, 4*(2), 204-230.

Potts, J., & Shehadeh, T. (2016). Over-Education in Australia's Creative Industries, working paper.

Potts, J., & Cunningham, S. (2008). Four models of the creative industries. *International Journal of Cultural Policy, 14*(3), 233-247.

Quingley, J. (1998). Urban diversity and economic growth. *Journal of Economic Perspectives, 2*, 127-38.

Rajan, S (2011). Moral Rights: Principles, Practice and New Technology. Oxford University Press: New York.

Rengers, M. (2002). Economic Lives of Artists: Studies into Careers and the Labour Market in the Cultural Sector. Utrecht University, Interuniversity Center for Social Science Theory and Methodology: Utrecht.

Rengers, M., & Madden, C. (2000). Living art: Artists between making art and making a living. *Australian Bulletin of Labour, 26*(4), 325.

Robinson, M. D., & Montgomery, S. S. (2000). The time allocation and earnings of artists. *Industrial Relations, 39*(3), 525–534.

Sacco, P. (1998). La selezione dei giovani artisti nei mercati delle arti visive. In W. Santagata (ed.), *Economia dell'arte*. UTET: Torino.

Senftleben, M. (2017). Copyright, Creators and Society's Need for Autonomous Art – The Blessing and Curse of Monetary Incentives. In R. Giblin, & K. Weatherall (eds.), *What if We Could Reimagine Copyright?* ANU Press: Canberra.

Serrà, J., Corral, A., Boguñá, M., Haro, M., & Arcos, J. (2012). Measuring the evolution of contemporary Western popular music. *Nature Scientific Reports*, 2(521).

Sicherman, N. (1991). Overeducation in the labor market. *Journal of Labor Economics, 9(*2), 101.

Simpson, C. (1981). SoHo: The Artist in the City. University of Chicago Press: Chicago.

Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics, 87*: 355– 74.

Steiner, L., & Schneider, L. (2013). The happy artist: An empirical application of the work-preference model. *Journal of Cultural Economics,37*(2), 225-246.

Stinchcombe, A. (1968). Constructing Social Theories. University of Chicago Press: Chicago.

Stoneman, P. (2015). Changes in Product Aesthetics, an Omitted Dimension in Economic Analyses of Innovation Activities. In D. Archibugi and A. Filippetti (eds.) *The Handbook of Global Science, Technology and Innovation Policy*, 88–108. Wiley Blackwell: Chichester.

Taylor, B. (1987). Artists in the marketplace: a framework for analysis. In D. Shaw, W Hendon, C.R. Waits (Eds.), Artists and Cultural Consumers. Akron: Assoc. for Cult. Econ.

Taylor, M., Marsh, G., Nicol, D., & Broadbent, P. (2017). Good Work, The Taylor Review of Modern Working Practices, Independent report commissioned by the UK government, London.

Terviö, M. (2009). Superstars and Mediocrities: Market Failure in The Discovery of Talent. *Review of Economic Studies, 72*(2), 829—850.

Throsby, D. & Thompson, B. (1994). But What do You do for a Living? A New Economic Study of Australian Artists, Australia Council, Redfern.

Throsby, D., & Zednik, A. (2010). Do you really expect to get paid? An economic study of professional artists in Australia. Strawberry Hills, NSW: Australia Council for the Arts.

Throsby, D. (1994). A Work-Preference Model of Artist Behaviour. In: Peacock A., Rizzo I. (eds.) *Cultural Economics And Cultural Policies*. Springer: Dordrecht.

Throsby, D. (1996). Disaggregated earnings functions for artists. In V. Ginsburgh, PM Menger (eds.), *Economics of the Arts*, 331-46. North Holland: Amsterdam.

Throsby, D., & Hollister, V. (2003). Don't Give Up Your Day Job: An Economic Study of Professional Artists in Australia. Australia Council: Sydney.

Towse, R. (1996a). The Economics of Artists Labor Markets. The Arts Council of England: London.

Towse, R. (1996b). Economics of Training Artists. In V.A. Ginsburgh, P.-M. Menger (eds.), Economics of the Arts: Selected Essays.

Towse, R. (2001). Partly for the Money: Rewards and Incentives to Artists. *Kyklos, 54*, 473-90.

Towse, R. (2006). Human Capital and Artists' Labour Markets. In V. Ginsburgh, Throsby, D. (eds.), *Handbook of the Economics of Art and Culture*, 1(24), 865–894. Elsevier: Amsterdam.

Towse, R. (2010). A textbook of cultural economics. Cambridge University Press: Cambridge.

Towse, R. (2014). Economics of performers' rights. In R. Watt (ed.) *Handbook on the Economics of Copyright*, 129-140, Edward Elgar Publishing.

Towse, R. (2018). Copyright reversion in the creative industries. *Columbia Journal of Law & the Arts*, 41, 467-489.

Tucker, C., & Zhang, J. (2007). Long Tail or Steep Tail? A Field. Investigation into How Online Popularity Information Affects the Distribution of Customer Choices. Working Paper no. 39811, Sloan School of Management, Massachusetts Institute of Technology.

United Kingdom Intellectual Property Office - UK IPO (2013).Evaluating the Impact of Parody on the Exploitation of Copyright Works: An Empirical Study of Music Video Content on YouTube, The Treatment of Parodies under Copyright in Seven Jurisdictions: A Comparative Review of the Underlying Principles, Copyright and the Economic Effects of Parody: An Empirical Study of Music Videos on the YouTube Platform and an Assessment of the Regulatory Options January 2013.

Waldfogel, J. (2012). Copyright Protection, Technological Change, and the Quality of New Products: Evidence from Recorded Music since Napster. *Journal of Law and Economics 55*(4), 715–40.

Waldfogel, J. (2016). Cinematic Explosion: New Products, Unpredictability, and Realized Quality in the Digital Era. *Journal of Industrial Economics 64*(4), 755–72.

Waldfogel, J. (2017a). How Digitization Has Created a Golden Age of Music, Movies, Books, and Television. *Journal of Economic Perspectives, 31*(3), 195-214.

Waldfogel, J. (2017b). The Random Long Tail and the Golden Age of Television. In S. Greenstein, J. Lerner, & S. Stern (eds.) *Innovation Policy and the Economy,* 1–25. National Bureau of Economic Research.

Waldfogel, J., & Reimers, I. (2015). Storming the Gatekeepers: Digital Disintermediation in the Market for Books. *Information Economics and Policy 31*, 47–58.

Zentner, A., Smith, M., & Kaya, C. (2013). How Video Rental Patterns Change as Consumers Move Online. *Management Science, 59*(11), 2622-2634.

Zhang, X., & Zhu, F. (2011). Group Size and Incentives to Contribute: A Natural Experiment at Chinese Wikipedia. *American Economic Review*, *101*(4), 1601-15.

ANNEX

Table A.1: Concordance table and selection of 4-digit International Standard Classification of Occupations (ISCO) 08 codes and selection of core art ones (printed in bold)

International Standard Classification of Occupations (ISCO) 08		Concordances			
Descriptor	4 digit Codes	International Standard Classification of Occupations (ISCO) 88	Classificacao Braileira de Ocupacoes (CBO) 2002	Sistema Nacional de Clasificación de Ocupaciones (SINCO) 2011	U.S. Census Code 2010
Sales and marketing managers	1221	1233, 1317	1233, 1417	1711	0050
Advertising and public relations managers	1222	1234	1423	1711	0060
Systems analysts	2511	2131	2123, 2124	2271	1005, 1006
Software developers	2512	2131	2123, 2124	2271	1020
Web and multimedia developers	2513	2131	2123, 2124	2271	1030
Building architects	2161	2141	2141	2263	1300
Town and traffic planners	2164	2141	2141	2132, 2263	1840
Librarians and related information professionals	2622	2432	2612	2144	2430, 2550
Archivists and curators	2621	2431	2613	2144	2400
Journalists	2642	2451, 3472	2611, 2617	2152	2810, 2830
Public relations professionals	2432	2451	2611	2112	2825
Advertising and marketing professionals	2431	2419	2531	2112	0735
Civil engineering technicians	3112	3112	3121	2624	1550, 1560
Visual artists	2651	2452	2624	2161	2600
Authors and related writers	2641	2451	2615	2151	2840, 2850
Actors	2655	2455	2623	2175	2700
Other arts teachers	2355	2359, 3340	3322, 3313	2712	2340, 2750
Musicians, singers and composers	2652	2453, 3473	2624	2171, 2172, 2173	2750
Film, stage and related directors and producers	2654	2455	2621, 2622, 2623	1421, 1721	2600, 2710, 2920
Photographers	3431	3131	2618	2655	2910
Broadcasting and audiovisual technicians	3521	3131	3721, 3741, 3742, 3744	2652, 2653, 2654	2900, 2920, 2960
Graphic and multimedia designers	2166	3471, 2452	3623, 3751, 2624	2543	2600, 2630
Product and garment designers	2163	3471	3751	2541, 2542	2630
Interior designers and decorators	3432	3471	3751	2544	2630
Advertising and marketing professionals	2431	2451, 2419	2531	2112	0735, 2850
Potters and related workers	7314	7321	7523, 8281	7611, 7612	8920
Countries	Denmark, Estonia	Denmark, Estonia, Germany, Russia	Brazil	Mexico	U.S.
Online sources (last accessed on July 30, 2018)		http://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm	http://www.mtecbo.gov.br/cbosite/pages/downloads.jsf	http://www.inegi.org.mx/est/contenidos/proyectos/aspectosmetodologicos/clasificadoresycatalogos/sinco.aspx	https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html

Source: Selected ISCO 08 codes based on previous research by Nathan et al (2015, 2016) and Bakhshi et al (2012). Note: Core art occupations based on authors' own selection and deployed in the EVS analysis' robustness checks.

Table A.2: Summary statistics by work status and group (creator sample dummy)

sample, any work status					
total population (creator sample = 0)					
Variable	Obs	Mean	Std. Dev.	Min	Max
gross total household income, upper decile and winsorized values	315	118850	168123	3691	943109
gross total household income, upper decile and winsorized values, ppp-adjusted and deflated (reference year 2011)	315	42878.52	35779.85	2772.829	151956
log gross total household income, upper decile and winsorized values, ppp-adjusted and deflated (reference year 2011)	315	10.29425	0.9205678	7.927623	11.93135
time	315	9.685714	3.39252	3	15
creator sample	315	0	0	0	0
real GDP, constant 2010 US-Dollars	315	6.59E+12	6.4E+12	22200000000	1.62E+13
log real GDP, constant 2010 US-Dollars	315	28.63217	1.732918	23.82266	30.41464
total number of households, weighted	315	64400000	42300000	574651.8	120000000
log total number of households, weighted	315	17.40466	1.523483	13.26152	18.6043
creators (creator sample = 1)					
gross total household income, upper decile and winsorized values	315	206055.2	271376.5	8584	1386211
gross total household income, upper decile and winsorized values, ppp-adjusted and deflated (reference year 2011)	315	70982.11	47160.8	5608.379	203775.3
log gross total household income, upper decile and winsorized values, ppp-adjusted and deflated (reference year 2011)	315	10.91395	0.7741238	8.632017	12.22477
time	315	9.685714	3.39252	3	15
creator sample	315	1	0	1	1
real GDP, constant 2010 US-Dollars	315	6.59E+12	6.4E+12	22200000000	1.62E+13
log real GDP, constant 2010 US-Dollars	315	28.63217	1.732918	23.82266	30.41464
total number of households, weighted	315	3032949	2222654	26899.12	6702566
log total number of households, weighted	315	14.24805	1.620306	10.19985	15.718
sample, self-employment only					
total population (creator sample = 0)					
gross total household income, upper decile and winsorized values	279	159140.9	233602	4140	1231188
gross total household income, upper decile and winsorized values, ppp-adjusted and deflated (reference year 2011)	279	62749.86	50867.86	1960.957	227423.7
log gross total household income, upper decile and winsorized values, ppp-adjusted and deflated (reference year 2011)	279	10.66351	0.9790454	7.581188	12.33457
time	279	9.806452	3.389334	3	15
creator sample	279	0	0	0	0
real GDP, constant 2010 US-Dollars	279	7.35E+12	6.41E+12	3.11E+11	1.62E+13
log real GDP, constant 2010 US-Dollars	279	28.98584	1.324877	26.46418	30.41464
total number of households, weighted	279	13000000	7985567	192596.7	28800000
log total number of households, weighted	279	15.86612	1.48275	12.16835	17.17589
creators (creator sample = 1)					
gross total household income, upper decile and winsorized values	279	191844.7	275731.1	9600	1546914
gross total household income, upper decile and winsorized values, ppp-adjusted and deflated (reference year 2011)	279	72479.97	52166.39	3135.642	238140
log gross total household income, upper decile and winsorized values, ppp-adjusted and deflated (reference year 2011)	279	10.9079	0.8151332	8.05059	12.38061
time	279	9.806452	3.389334	3	15
creator sample	279	1	0	1	1
real GDP, constant 2010 US-Dollars	279	7.35E+12	6.41E+12	3.11E+11	1.62E+13

log real GDP, constant 2010 US-Dollars	279	28.98584	1.324877	26.46418	30.41464
total number of households, weighted	279	689000.1	419037.9	2119.108	1220576
log total number of households, weighted	279	12.78712	1.817258	7.658751	14.01483

Source: Based on author calculations and LIS/IPUMS data. Note: For self-employed individuals, limited or no data available for Russian, Estonian and German samples.

Table A.3: Summary statistics by model specification and group (creator sample dummy)

sample, all ISCO codes					
variable	Obs	Mean	Std. Dev.	Min	Max
income regression					
total population (creator sample = 0)					
monthly household income	37,549	1.306933	1.235197	0.0322018	14.72816
monthly household income, ppp-adjusted, deflated (reference year 2010) and windsorized	37,549	1.234588	1.174681	0.0314078	14.36501
log monthly household income, ppp-adjusted, deflated (reference year 2010) and windsorized	37,549	-0.1926127	0.9548091	-3.460699	2.664795
creator sample	37,549	0	0	0	0
time, 4th wave dummy	37,549	0.5745825	0.4944127	0	1
self-employed	37,549	0.0470585	0.2117669	0	1
female	37,549	0.5632107	0.4959949	0	1
age	37,549	48.18826	17.67432	16	103
single household	37,549	0.2175025	0.4125526	0	1
real GDP, constant 2010 US-Dollars	37,549	7.95E+11	1.02E+12	1.28E+10	3.48E+12
creators (creator sample = 1)					
monthly household income	997	1.935701	1.566189	0.0357101	11.13891
monthly household income, ppp-adjusted, deflated (reference year 2010) and windsorized	997	1.841164	1.501049	0.0348296	10.86426
log monthly household income, ppp-adjusted, deflated (reference year 2010) and windsorized	997	0.2590455	0.9149477	-3.357288	2.385478
creator sample	997	1	0	1	1
time, 4th wave dummy	997	0.6298897	0.4830763	0	1
self-employed	997	0.1675025	0.3736113	0	1
female	997	0.4282849	0.4950786	0	1
age	997	45.34102	14.84086	18	90
single household	997	0.2477432	0.4319186	0	1
real GDP, constant 2010 US-Dollars	997	8.34E+11	9.87E+11	1.28E+10	3.48E+12
job satisfaction regression					
total population (creator sample = 0)					
job satisfaction, Likert scale	19,403	7.239293	2.133736	1	10
creator sample	19,403	0	0	0	0
time, 4th wave dummy	19,403	0.564088	0.4958885	0	1
self-employed	19,403	0.0846776	0.2784086	0	1
female	19,403	0.5057465	0.4999799	0	1
age	19,403	41.09504	12.02257	17	103
single household	19,403	0.2465598	0.4310193	0	1
real GDP, constant 2010 US-Dollars	19,403	7.65E+11	9.92E+11	1.28E+10	3.48E+12
creators (creator sample = 1)					
job satisfaction, Likert scale	777	7.597169	1.790911	1	10
creator sample	777	1	0	1	1
time, 4th wave dummy	777	0.6061776	0.488911	0	1
self-employed	777	0.2033462	0.4027472	0	1
female	777	0.4092664	0.4920152	0	1
age	777	41.33462	11.66671	18	84
single household	777	0.2805663	0.4495653	0	1
real GDP, constant 2010 US-Dollars	777	8.47E+11	9.76E+11	1.28E+10	3.48E+12

sample, core ISCO codes					
income regression					
total population (creator sample = 0)					
monthly household income	37,955	1.316937	1.245521	0.0322018	14.72816
monthly household income, ppp-adjusted, deflated (reference year 2010) and windsorized	37,955	1.244355	1.185	0.0314078	14.36501
log monthly household income, ppp-adjusted, deflated (reference year 2010) and windsorized	37,955	-0.1857523	0.9560254	-3.460699	2.664795
creator sample	37,955	0	0	0	0
time, 4th wave dummy	37,955	0.5760769	0.4941849	0	1
self-employed	37,955	0.0485048	0.2148332	0	1
female	37,955	0.5601107	0.4963801	0	1
age	37,955	48.12657	17.647	16	103
single household	37,955	0.2182058	0.4130333	0	1
real GDP, constant 2010 US-Dollars	37,955	7.97E+11	1.02E+12	1.28E+10	3.48E+12
creators (creator sample = 1)					
monthly household income	591	1.725145	1.389215	0.0357101	8.37
monthly household income, ppp-adjusted, deflated (reference year 2010) and windsorized	591	1.630655	1.32145	0.0348296	8.163623
log monthly household income, ppp-adjusted, deflated (reference year 2010) and windsorized	591	0.1287352	0.9351889	-3.357288	2.099688
creator sample	591	1	0	1	1
time, 4th wave dummy	591	0.571912	0.4952208	0	1
self-employed	591	0.1573604	0.3644487	0	1
female	591	0.534687	0.4992179	0	1
age	591	47.34687	15.22041	19	90
single household	591	0.2233503	0.416844	0	1
real GDP, constant 2010 US-Dollars	591	7.68E+11	9.35E+11	1.28E+10	3.48E+12
job satisfaction regression					
total population (creator sample = 0)					
job satisfaction, Likert scale	19,745	7.24239	2.128232	1	10
creator sample	19,745	0	0	0	0
time, 4th wave dummy	19,745	0.5660674	0.4956284	0	1
self-employed	19,745	0.0866548	0.2813357	0	1
female	19,745	0.5017979	0.5000094	0	1
age	19,745	41.06685	12.01038	17	103
single household	19,745	0.2478096	0.4317516	0	1
real GDP, constant 2010 US-Dollars	19,745	7.68E+11	9.93E+11	1.28E+10	3.48E+12
creators (creator sample = 1)					
job satisfaction, Likert scale	435	7.737931	1.78713	1	10
creator sample	435	1	0	1	1
time, 4th wave dummy	435	0.5494253	0.498124	0	1
self-employed	435	0.2068966	0.4055471	0	1
female	435	0.5126437	0.5004156	0	1
age	435	42.8023	11.82992	19	84
single household	435	0.2505747	0.433843	0	1
real GDP, constant 2010 US-Dollars	435	7.79E+11	9.22E+11	1.28E+10	3.48E+12

Source: Based on author calculations and EVS data.

Table A.4: Summary statistics by model specification and group (non-art occupation dummy)

income bands regression					
non-art occupation (non-art occupation dummy = 1)					
Variable	Obs	Mean	Std. Dev.	Min	Max
individual annual income (bands)	62,414	6.555196	3.136575	2	13
time	62,414	3.418896	1.818283	1	6
non-art occupation dummy	62,414	0	0	0	0
Architecture	62,414	0.05816	0.2340477	0	1
Art History	62,414	0.0256833	0.1581901	0	1
Arts Administration	62,414	0.0083956	0.0912425	0	1
Arts Education	62,414	0.0864069	0.2809662	0	1
Creative and Other Writing	62,414	0.0097574	0.0982974	0	1
Dance	62,414	0.020332	0.1411344	0	1
Design	62,414	0.158394	0.3651129	0	1
Fine and Studio Arts	62,414	0.2655174	0.4416118	0	1
Media Arts	62,414	0.0945621	0.2926115	0	1
Theater	62,414	0.0877047	0.2828672	0	1
Music	62,414	0.1756337	0.3805112	0	1
Craft	62,414	0.009453	0.0967667	0	1
real GDP, constant 2010 US-Dollars	62,414	1.57E+13	5.92E+11	1.50E+13	1.66E+13
art or art-related occupation (non-art occupation dummy = 0)					
individual annual income (bands)	29,989	6.68992	3.34918	2	13
time	29,989	3.345927	1.870466	1	6
non-art occupation dummy	29,989	1	0	1	1
Architecture	29,989	0.0353796	0.1847405	0	1
Art History	29,989	0.0484511	0.214721	0	1
Arts Administration	29,989	0.0151722	0.1222396	0	1
Arts Education	29,989	0.0580546	0.2338506	0	1
Creative and Other Writing	29,989	0.0294775	0.1691435	0	1
Dance	29,989	0.0294775	0.1691435	0	1
Design	29,989	0.0904332	0.2868061	0	1
Fine and Studio Arts	29,989	0.257361	0.4371873	0	1
Media Arts	29,989	0.1078395	0.3101828	0	1
Theater	29,989	0.1360832	0.3428826	0	1
Music	29,989	0.183734	0.3872736	0	1
Craft	29,989	0.0085365	0.0919993	0	1
real GDP, constant 2010 US-Dollars	29,989	1.57E+13	6.09E+11	1.50E+13	1.66E+13
income concentration regression					
non-art occupations (non-art occupation dummy = 1)					
income concentration (normalized entropy)	57	0.9392421	0.0378463	0.8020363	0.9902923
time	57	3.473684	1.881349	1	6
non-art occupation dummy	57	0	0	0	0
real GDP, constant 2010 US-Dollars	57	1.57E+13	6.17E+11	1.50E+13	1.66E+13
art or art-related occupations (non-art occupation dummy = 0)					
income concentration (normalized entropy)	57	0.9574606	0.0248032	0.8743291	0.9881691
time	57	3.473684	1.881349	1	6
non-art occupation dummy	57	1	0	1	1
real GDP, constant 2010 US-Dollars	57	1.57E+13	6.17E+11	1.50E+13	1.66E+13

Source: Based on author calculations and SNAAP data.

Table A.5: Summary statistics by model specification and group (early stage creator dummy)

Variable	Obs	Mean	Std. Dev.	Min	Max
sample, total insured (early stager dummy = 0)					
income regression					
individual annual income from self-employed art work, nominal	10,166	11855.44	4093.869	2000	64934
individual annual income from self-employed art work, deflated (reference year 2010)	10,166	119.6144	39.52189	20.28398	701.9892
log individual annual income from self-employed art work, deflated (reference year 2010)	10,166	4.734099	0.3146049	3.009831	6.553918
year	10,166	2009.003	4.320485	2002	2016
early stager dummy	10,166	0	0	0	0
fine arts	10,166	0.2500492	0.4330624	0	1
performing arts	10,166	0.2502459	0.4331759	0	1
music	10,166	0.2508361	0.4335157	0	1
writing/literature	10,166	0.2488688	0.4323789	0	1
below 30	10,166	0.1986032	0.3989682	0	1
30-40	10,166	0.2006689	0.4005205	0	1
40-50	10,166	0.2006689	0.4005205	0	1
50-60	10,166	0.2006689	0.4005205	0	1
above 60	10,166	0.1993901	0.3995615	0	1
gender (male)	10,166	0.5003935	0.5000244	0	1
real GDP, constant 2010 Euros	10,166	26.18813	1.321612	24.77768	29.27421
number insured regression					
number of insured	10,167	234.5618	340.9265	1	2496
log number of insured	10,167	4.503437	1.518707	0	7.822445
year	10,167	2009.003	4.320375	2002	2016
early stager dummy	10,167	0	0	0	0
fine arts	10,167	0.2500246	0.4330482	0	1
performing arts	10,167	0.2503197	0.4332184	0	1
music	10,167	0.2508114	0.4335015	0	1
writing/literature	10,167	0.2488443	0.4323647	0	1
below 30	10,167	0.1985837	0.3989534	0	1
30-40	10,167	0.2006492	0.4005057	0	1
40-50	10,167	0.2006492	0.4005057	0	1
50-60	10,167	0.2006492	0.4005057	0	1
above 60	10,167	0.1994689	0.3996208	0	1
gender (male)	10,167	0.5003443	0.5000245	0	1
real GDP, constant 2010 Euros	10,167	26.18806	1.321565	24.77768	29.27421
sample, early stagers (early stager dummy = 1)					
income regression					
individual annual income from self-employed art work, nominal	8,545	10076.08	6000.078	100	96000
individual annual income from self-employed art work, deflated (reference year 2010)	8,545	101.7942	59.03906	1.064963	1022.364
log individual annual income from self-employed art work, deflated (reference year 2010)	8,545	4.508536	0.4682833	0.0629398	6.929873
year	8,545	2008.851	4.277152	2002	2016
early stager dummy	8,545	1	0	1	1
fine arts	8,545	0.2531305	0.4348305	0	1
performing arts	8,545	0.2303101	0.421056	0	1
music	8,545	0.2527794	0.434631	0	1
writing/literature	8,545	0.26378	0.4407072	0	1
below 30	8,545	0.2321826	0.4222496	0	1
30-40	8,545	0.2375658	0.4256166	0	1
40-50	8,545	0.229842	0.4207557	0	1

50-60	8,545	0.2098303	0.4072112	0	1
above 60	8,545	0.0905793	0.2870267	0	1
gender (male)	8,545	0.506495	0.4999871	0	1
real GDP, constant 2010 Euros	8,545	26.13623	1.288775	24.77768	29.27421
number insured regression					
number of insured	8,554	30.29518	55.56145	1	744
log number of insured	8,554	2.378332	1.476737	0	6.612041
year	8,554	2008.848	4.277166	2002	2016
early stager dummy	8,554	1	0	1	1
fine arts	8,554	0.2533318	0.4349447	0	1
performing arts	8,554	0.2301847	0.4209756	0	1
music	8,554	0.2527473	0.4346127	0	1
writing/literature	8,554	0.2637363	0.4406837	0	1
below 30	8,554	0.2318214	0.4220202	0	1
30-40	8,554	0.2373159	0.4254624	0	1
40-50	8,554	0.2297171	0.4206755	0	1
50-60	8,554	0.2098433	0.4072205	0	1
above 60	8,554	0.0913023	0.2880554	0	1
gender (male)	8,554	0.5061959	0.4999908	0	1
real GDP, constant 2010 Euros	8,554	26.13552	1.289129	24.77768	29.27421

Source: Based on author calculations and KSK data. Note: KSK defines 'early stages' as the first three years after starting artistic self-employment.

Table A.6: Estimation results (OLS) and robustness checks reporting coefficients and standard errors for income levels, by any work status and by self-employed only

Sample	**any work status**		**self-employment only**			
Variable	**DV: log household income**		**DV: log household income**			
Model	(1)	(2)	(3)	(4)	(5)	(6)
time	0.011***		-0.002		-0.004*	
	0.002		0.003		0.002	
time (total population)		0.005		-0.011**		-0.002
		0.003		0.004		0.002
time (creators)		0.016***		0.006		-0.006**
		0.003		0.004		0.002
creator sample	0.620***	0.510***	0.244***	0.077	-0.693***	-2.366***
	0.013	0.039	0.017	0.051	0.045	0.127
log supply					-0.304***	
					0.014	
log supply (total population)						-0.437***
						0.016
log supply (creators)						-0.334***
						0.013
decile FE	yes	yes	yes	yes	yes	yes
country FE	yes	yes	yes	yes	yes	yes
const.	9.993***	10.048***	11.212***	11.296***	16.163***	18.275***
	0.041	0.044	0.053	0.057	0.235	0.252
N	630	630	558	558	558	558
adj R2	0.968	0.969	0.953	0.954	0.974	0.981

legend: * p<.05; ** p<.01; *** p<.001

Source: Based on author calculations and LIS/IPUMS data. Note: For self-employed individuals, limited or no data available for Russian, Estonian and German samples.

Table A.7: Estimation results (OLS) and robustness checks reporting coefficients and standard errors for income and job satisfaction levels, by all and core occupational codes

Sample	all ISCO codes		core ISCO codes	
Variable	**DV: log household income**	**DV: job satisfaction**	**DV: log household income**	**DV: job satisfaction**
Model	(1)	(2)	(3)	(4)
time (creators)	0.140**	-0.17	0.074	-0.205
	0.043	0.152	0.055	0.2
time (total population)	0.132***	0.124***	0.135***	0.122***
	0.008	0.032	0.007	0.032
creator sample	0.122	0.551	0.14	0.105
	0.086	0.343	0.114	0.463
log income (creators)		0.331***		0.233*
		0.086		0.115
log income (total population)		0.426***		0.428***
		0.023		0.023
self-employed (creators)	-0.017	-0.139	-0.015	-0.327
	0.053	0.176	0.074	0.249
self-employed (total population)	0.192***	0.412***	0.193***	0.395***
	0.016	0.053	0.015	0.052
female (creators)	-0.079	0.207	-0.093	0.343
	0.042	0.151	0.054	0.2
female (total population)	-0.115***	0.017	-0.117***	0.014
	0.007	0.029	0.007	0.029
age (creators)	-0.011***	0.004	-0.012***	0.016
	0.002	0.007	0.002	0.009
age (total population)	-0.014***	0.007***	-0.014***	0.006***
	0	0.001	0	0.001
single hh (creators)	-0.220***	-0.139	-0.327***	0.157
	0.052	0.178	0.07	0.244
single hh (total population)	-0.290***	-0.078*	-0.288***	-0.086*
	0.009	0.039	0.009	0.038
country FE	yes	yes	yes	yes
const.	0.434***	6.976***	0.436***	7.001***
	0.024	0.113	0.024	0.112
N	39897	21086	39897	21086
adj. R2	0.525	0.057	0.523	0.058

Source: Based on author calculations and EVS data.

Table A.8: Estimation results (OLS) and robustness checks reporting coefficients and standard errors for income levels and concentration of income

Variable	DV: individual income (bands)	DV: income concentration (entropy)
Model	(1)	(2)
time (non-art occ.)	0.129***	0
	0.01	0.002
time (art occ.)	0.070***	0.004*
	0.007	0.002
non-art occ. dummy	0.07	0.029**
	0.046	0.009
majors dummies		
Architecture	2.044***	0.029*

	0.111	0.014
Art History	-0.044	0.009
	0.116	0.014
Arts Administration	reference category	-0.014
		0.014
Arts Education	0.602***	0.021
	0.107	0.014
Creative and Other Writing	-0.491***	-0.019
	0.13	0.014
Dance	-0.469***	-0.011
	0.121	0.014
Design	1.181***	0.047***
	0.105	0.014
Fine and Studio Arts	-0.132	0.021
	0.103	0.014
Media Arts	0.760***	0.047***
	0.106	0.014
Theater	0.330**	0.035*
	0.106	0.014
Music	0.521***	0.041**
	0.104	0.014
Craft	-0.136	reference category
	0.148	
const.	5.817***	0.909***
	0.104	0.014
N	92403	114
adj. R2	0.037	0.53

Source: Based on author calculations and SNAAP data.

Table A.9: Estimation results (OLS) and robustness checks reporting coefficients and standard errors for real income levels and total number of KSK insured and by career stage

sample	**total insured**		**early stagers**	
variable	**DV: log income**	**DV: log number insured**	**DV: log income**	**DV: log number insured**
model	(1)	(2)	(3)	(4)
time (fine arts)	0.017***	0.026***	0.020***	-0.069***
	0.001	0.005	0.002	0.005
time (performing arts)	0.010***	0.048***	0.004*	-0.047***
	0.001	0.005	0.002	0.005
time (music)	0.007***	0.046***	0.003	-0.076***
	0.001	0.005	0.002	0.005
time (writing)	0.015***	0.031***	0.020***	-0.066***
	0.001	0.005	0.002	0.005
art category				
fine arts	-0.321***	0.545***	-0.380***	0.069
	0.015	0.079	0.031	0.08
performing arts	-0.225***	-0.671***	-0.297***	-0.987***
	0.015	0.079	0.032	0.083
music	-0.277***	0.165*	-0.305***	-0.093
	0.015	0.079	0.031	0.08
writing	reference category			

gender (male)	0.240***	0.205***	0.198***	-0.176***
	0.004	0.022	0.009	0.023
age: below 30	-0.279***	-0.835***	0.023	2.239***
	0.007	0.036	0.017	0.046
30-40	-0.131***	1.148***	0.052**	3.079***
	0.007	0.035	0.017	0.046
40-50	0.013	1.510***	0.081***	2.135***
	0.007	0.035	0.017	0.046
50-60	0.056***	1.100***	0.068***	1.224***
	0.007	0.035	0.018	0.047
above 60		reference category		
const.	4.765***	3.420***	4.480***	1.341***
	0.012	0.061	0.026	0.068
N	10166	10846	8545	9066
adj. R2	0.518	0.409	0.232	0.43
				legend: * p<.05; ** p<.01; *** p<.001

Source: Based on author calculations and KSK data. Note: KSK defines ‘early stages’ as the first three years after starting artistic self-employment.

1 Evidence from previous research on income and the distribution of income is mixed and often predates the online world (for example, Filer 1986, Throsby 1994, or Potts and Cunningham 2008).

2 For example, removal of some of the barriers to entry (and some of the market power) can be viewed as positive from a welfare economic perspective, as they make markets more contestable. It might help total investment on markets and limit the extent of market failure due to the public good features of creative works and the positive externalities these generate. Moreover, greater market entry has implications for diversity, another frequent cited goal of policies.

3 Among other things, it does not consider the various indirect effects on creators' employment and income over time, i) gains or losses in industry revenue due to sales displacement due to unauthorized copying and use of works in some sectors, ii) industrial change and effects from 'creative destruction' in the industries due to the emergence of new technology, online service providers and experimentation with new business models, among other things, iii) related demand changes and new modes of consumption (for example, streaming in music and film), or, iv) changes in bargaining positions and allocation of revenues in value chains. Issues of possible 'disintermediation' in the digital environment – where, for example, online crowdfunding making up-front development and marketing costs more affordable for individual artists and facilitating liaisons with fans and supporters – arguably, constitute a borderline case which for reasons of scope are excluded from this study.

4 More recent evidence suggests that educational attainment has a positive effect on survival in certain arts occupations, but not in all (for Danish artists, see Bille and Jensen 2018). However, this research provides no evidence on income effects. Other economic modelling (Spence 1973) implies a 'credential signalling' of high-ability artists (if aware of their own type) to employers as a form of strategic 'over-investment' (in education, Sicherman 1991), in order to overcome the information asymmetries described above. However, empirical evidence on such signalling in Australian artistic labor markets suggests that creative sectors may be facing an under-education rather than over-education issue, where (if any) over-education is greatest amongst the older artist cohorts rather than younger ones, and tends to be concentrated in creative employment outside creative industries (Potts and Shehadeh 2016).

5 'Diversified workers' are workers that generate income from multiple sources and a mix of traditional employment and freelance work. 'Independent contractors' are workers that do all their work on a project-to-project basis.

6 Arguably, official statistics are less capable of capturing these types of online work arrangements whenever arrangements do not comply with survey standards used to define self-employment and holding of multiple jobs, for example, in US household surveys (see: https://www.bloomberg.com/view/articles/2017-10-17/the-rise-of-the-not-just-freelancing-freelancer). However, the BLS Contingent Worker Surveys is a supplement to the monthly U.S. Current Population Survey (CPS) and attempts to fill these measurement gaps. It aims to account for alternative employment arrangements such as independent contractors, on-call workers, temporary help workers, and contract company workers.

7 Again, one of Araujo's (2013) findings that the quality of designs as rated by platform users increases with the total number of designers attracted to a contest relates to this idea. However, the research does not explicitly control for the location of designers.

8 More specifically, the cost of digital SLR (single-lens reflex) cameras, using interchangeable lenses and capable of shooting high-definition video, is approximately one percent of the price of pre-existing distribution-quality film cameras and the former are available for a few thousand U.S. dollars (Waldfogel 2016).

9 Nathan et al (2015, 2016) and Bakhshi et al (2012) are examples using occupational codes. However, their focus is on the identification of industries with high 'intensity' in terms of creative occupations employment and measuring the size of these industries.

10 For self-employed creators in Danish and Estonian samples, selection of self-employed individuals is based on first job information only, as second job information on work status is not available in the LIS data.

11 More specifically, we replace or bottom-code negative reported income values by zeros and top-code income values larger than ten times the distribution's median.

12 This slightly differs from the commonly used 'disposable household income' definition and our choice aims to limit the effects from taxes/tax redistribution policies. However, the latter comes at the cost of data coverage as

we cannot include any of the LIS dataset from countries flagged as net income sources. Relevant to copyright policies, gross total income includes, among many other sources of income, capital income from royalties.

13 When analyzing self-employed individuals, we have to eliminate all Russian and Estonian annual samples in our LIS data because of very low numbers of observations identifying self-employed creators.

14 The final data include survey responses from the following countries: Austria, Bulgaria, Belarus, Czech Republic, Germany, Estonia, Great Britain, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Russia, Slovakia and Ukraine.

15 A Likert scale is a psychometric response scale to obtain respondent's preferences or degree of agreement with a statement. For example, this could be a 10-point scale ranging from 'strongly disagree' on one end to 'strongly agree' on the other with 'neither agree nor disagree' in the middle.

16 The twelve income bands structure in the following way, '$10,000 or less', '$10,001 to $20,000', '$20,001 to $30,000', …, '$90,001 to $100,000', '$100,001 to $150,000' and 'more than $150,000'.

17 In order to finance public co-financing taxes are being collected from entities commissioning out/outsourcing work to self-employed creators such as marketing companies, museums, theatres, publishers, etc.

18 Notably, on the basis of the EVS data we cannot study income concentration, as sample sizes for those identified as creators are too low.

19 Upon request, we also provide estimation results based on ordinal logistic regressions.

20 We insert logged real GDP in constant 2010 US-Dollars to all models, accounting for cyclical effects on income and satisfaction.

21 Hence, we do not have to rely on occupational code selection in this analysis, even though this may limit comparability across the various data sources and various analyses in the report. Also note that the major field of 'craft' data are only available for the last two waves of the SNAAP survey data we can access.

22 The data, even though these are large survey samples of alumni, are limited in their capacity to credibly illustrate changes in representative/total supply and entry of creators to artistic labor markets.

23 Upon request we also provide estimation results based on ordinal logistic regressions.

24 We use STATA's divcat package to run calculations.

25 Above a certain income/net revenue threshold, self-employed artists (as applicable to all self-employed persons in Germany) may choose to opt out of the KSK public insurance scheme into a private, high-cost one. From 2015 to 2017, this threshold was 168,750 Euros for high earners. For young professional, similar exit options exist. In turn, this suggests that the data less well covers particular groups of creators because their incentives to participate in the scheme are less stringent. If many opt out, this may impose certain bias to averages observed. However, we are not aware of any substantial changes in legal thresholds and incentives over time – those provided within and outside the insurance scheme – that would systematically bias time trends. Note also that the selection of ISCO codes used in the LIS data is in any case broader and covers a greater variety of creative occupations than the few, non-standardized/proprietary categories used by KSK officials.

26 Further analysis focusing on time trends in age cohorts (available from the authors upon request) seems to confirm our basic intuition: all cohorts above the age of 40 evidence positive and increasing trends in the total insured population over time (specification 2), while younger cohorts render insignificant, with older artists staying active over longer periods of time. However, losses in new entry, i.e. negative time trends, can be found across all age cohorts.

27 Previous research on wage effects does not see the skill biased technological change model confirmed in Germany (Lucchese and Bogliacino 2011), research also using LIS data, the German re-unification as a natural experiment and a broader definition of 'abstract jobs' than the one we use, our research targeting creators only.

28 However, these studies are not able to establish causal effects, nor control for plausible endogeneity issues, i.e. certain legal systems being more likely than others to introduce provisions, depending on the income situation of creators in each jurisdiction. Clearly, more research will need to be done in this interesting area.

29 Focusing on self-employed creators only in the LIS data, as many creators are self-employed as regards income trends over time and differences in these trends. Using alternative national data sources such as the Strategic National Arts Alumni Project (SNAAP) in the United States and the German social insurance scheme 'Kuenstlersozialkasse' (KSK) with varying control groups yields similar results and mostly confirms positive (but below GDP growth) income trends for creators in various disciplines. Analysis based on the European Value Survey (EVS) does not seem to confirm overall results. However, these data are not fully comparable to the LIS data at the outset.

30 We cannot fully rule out the possibility that the 'compound' time trend effect we observe is the outcome of a positive wage effect (from skill-biased technological changes) and, arguably, a decline in income among creators with more online uses ('value gap' effect). However, note again, the data sources that allow us to distinguish specific artistic categories, including music, do not suggest that time trend effects in categories with higher online exposure, such as music, are systematically different from those with lower online exposure, such as the performing arts.

31 The role of attributing works and value of moral rights to creators have been discussed and researched in various places (Rajan 2011; Towse 2001), with results calling into question whether a purely profit-based theory of copyright law is sufficient and whether moral rights should differ across copyright systems (Bechtold and Engel 2017).

32 An interesting example is Abbing (2004). In line with the basic work-preference model (Throsby 1994), he shows that cultural policies render ineffective due to the variety of motivators and a strong preference for art practicing that drive creators, particularly visual artists. Another example is Buccafusco and Sprigman (2011) who discuss 'creativity biases' and propose to take greater account of work-for-hire rules in legal frameworks as a result (see the discussion in the literature review for further details on this type of bias).

33 In other words, genuinely new varieties generated by avant-garde artists might affect the pace of 'recombinant growth' we observe (Fleming 2001), even though it may be practically impossible to draw the line on what constitutes genuinely 'new' content. Conceptualizing 'recombination' as a combinatorial search for creation and innovation, as done in Fleming, learning opportunities may exhaust as fewer useful innovations remain in the search space.

34 An interesting discussion of sequential creation as well as the contextual, legal and economic factors is provided in Buccafusco et al (2017).