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Individualism, Creativity, and Innovation

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Individualism, Creativity, and Innovation

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Abstract

Individualist societies are more innovative, but little is known about the underlying individual behaviors. I use international labor-market and patent data to show that individualism—the cultural dimension that emphasizes individual achievements over collective action—positively affects individual innovation. Comparing migrants from different cultural origins within the same destination country and using variation in individualism at the country, region, and person level, I find that more individualist migrants select into more innovative occupations—including research, creative jobs, and ambitious entrepreneurship. Individualists also engage more readily in knowledge diffusion on the job—even when accounting for occupational selection—by investing more time in active learning. Taken together, those innovation choices account for 44 percent of the individualism productivity premium. Individualism also positively affects patenting behavior as a direct innovation output measure.

Keywords: culture; individualism; innovation; knowledge diffusion; patents; labor market

JEL: O31, D91, J24, Z13

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I. Introduction

Individualism is the cultural driving force behind long-run growth (Gorodnichenko and Roland 2011a, 2011b, 2017). Since this culture of personal freedom and responsibility rewards stand-out achievements and uniqueness, innovation as a key growth determinant (Romer 1990; Mokyr 2009; Sampson 2023) has long been considered a main mechanism behind the growth effects. To investigate the innovation-based mechanism, economists have thus far focused on very narrow measures of innovation that largely capture structured scientific knowledge: Patents at the aggregate and research occupations at the individual level (Gorodnichenko and Roland 2017; Hartinger et al. 2021).[1] In contrast, although entrepreneurs are often portrayed as the epitome of individualism, evidence on entrepreneurship has been ambiguous and context-dependent (Hofstede et al. 2004; Nikolaev, Boudreaux, and Palich 2018; Barrios, Hochberg, and Macciocchi 2021; Mostaghel, Oghazi, and Patel 2023). This tension underlines how important it is to deepen our understanding of the role of individualism in individual innovation—in particular, by analyzing its effects on the full growth-relevant innovative potential of individuals in a society (Phelps 2013, 2018).

This paper is the first to investigate how individualism affects individual innovation behaviors internationally and *comprehensively*—spanning technological-inventive, economic-entrepreneurial, and cultural-artistic creativity (Florida 2002)—and to show that these behaviors translate directly into individual productivity differences. To do so, I compare migrants from different cultural backgrounds within the same destination country using international skills test and labor market data from the OECD's Programme for the Assessment of Adult Competences (PIAAC) as well as patent data from the Patent Cooperation Treaty (PCT; Miguélez and Fink 2013) and data from the German Socioeconomic Panel (SOEP).

Since individualism forms part of a person's cultural toolkit (Swidler 1986; Hofstede 2001)—as an innate cultural trait that is passed on within the family fairly unchanged from generation to generation (Guiso, Sapienza, and Zingales 2006)—, the analysis focuses on the inventors, creatives, and entrepreneurs behind the innovation: I document substantial individualism-driven selection into innovative occupations by looking at several classifications of artistic and creative occupations (i.e., Florida 2002) and ambitious[2] self-employment. More individualist people are also significantly more likely to actively choose a learning- and innovation-focused approach to their job even within a given occupation, which is related to the diffusion stage of the innovative process (Schumpeter 1911, 1942) where know-how is passed on.

After establishing the implications of individualism for career-related innovation behaviors, I study their role in explaining individual productivity differences in a mediation

[1] Only seven percent of occupations in OECD countries fall into the research category, an international adult survey (PIAAC) shows.

[2] Defined here as self-employment in the innovative sector.

analysis. Together, the selection into creative occupations and the diffusion of knowledge on the job through learning account for almost half of the individualism productivity premium. Thus, individualism-induced individual innovation behaviors explain a significant share of productivity differences between individuals with different individualism levels. Finally, when looking at patenting behavior as a direct innovation outcome measure, I find that migrants from a more individualist background patent significantly more often, confirming the importance of individualism for innovative output at the inventor level.

These results support a strong and positive relationship between individualism and individual innovativeness. This is in line with individualism theory, which predicts that the societal rewards for independence, personal achievements, and uniqueness will manifest themselves at the individual level as strong motivators for innovative behavior as a way of reaching self-fulfillment through career achievements (see Section II.A for details regarding the individual-level mechanisms). Thus, this paper is also the first to provide a comprehensive micro-foundation of the established growth effects through innovation. Each dimension of innovation studied here has specific implications for growth ranging from the expansion of the scientific-technological frontier to accumulation of knowledge capital and the attraction of talent (see Section II.B.). Moreover, previous findings related to individualism and innovation would be consistent with the notion of individualism-driven innovation as a phenomenon that only applies to a specific, small subgroup of the population that patents and works in research. Understanding whether individualism is indeed a "Silicon Valley Superstar" phenomenon or whether it increases the broad innovativeness of a society as conceptualized by Phelps (2013) is only possible by considering more inclusive measures of innovation and productivity. A simple country-level correlation in Figure 1 summarizes the motivation behind such a broad individual-level perspective on the effect of individualism on innovation: Individualism is strongly positively related to country-level creativity. Thus, there are innovation implications of individualism beyond patents and science, which makes a holistic perspective worthwhile.

When investigating effects of culture on individual economic outcomes, the so-called *epidemiological approach* is the most established strategy. In this approach, migrants from different cultural backgrounds are compared within the same destination country—holding constant their current institutional and economic environment. Since migrants have been found to affect innovation in both origin and destination countries, they are a particularly interesting sample in the context of innovation (Andersson, Karadja, and Prawitz 2022; Azoulay et al. 2022; Bernstein et al. 2022).

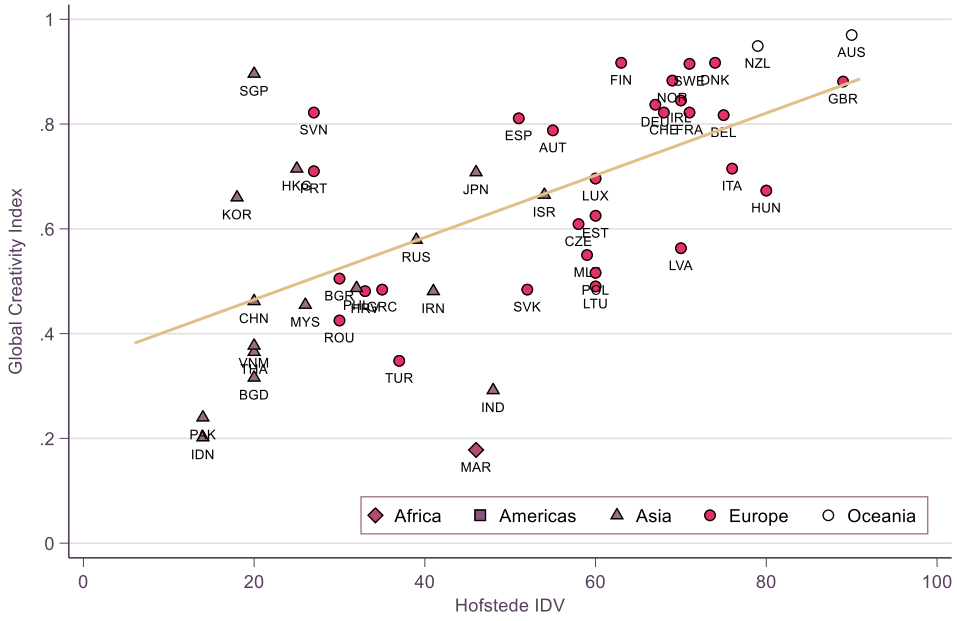

Figure 1. Motivating Evidence

Notes: The figure shows the raw country-level correlation between Hofstede individualism and the 2015 Global Creativity Index. *Data sources:* Hofstede (2001), Global Creativity Index.

The key assumption is that a migrant's original cultural toolkit still affects their decision-making in the destination country, which has been shown in the literature on cultural persistence across space and time (Fernández and Fogli 2009; Figlio et al. 2019). In this framework, individualism is measured via the origin-country Hofstede (2001) individualism score for each migrant based on Hofstede's IBM employee surveys from the 1960s and 70s (and replications) that underly his conceptualization of culture.

Focusing on career-related innovation behaviors first, I find that migrants from more individualist backgrounds also choose more creative-innovative occupations based on rich labor market data from PIAAC for more than 4,500 first-generation migrants living in 25 destination countries. More individualist migrants are significantly more likely to work in *creative occupations* as conceptualized by Cruz and Teixeira (2014) (an increase of 8.0 percentage points or 19 percent relative to baseline for a one-standard-deviation increase in individualism) and as *performing artists* (0.7 percentage points or 70 percent). Even within occupation, individualists engage more frequently in knowledge diffusion and adoption behaviors that bring them closer to the technological frontier: They spend significantly more time *learning by doing*, *keeping up-to-date*, and *learning from coworkers*. Using data from the 2017-2019 waves of the German Socioeconomic Panel, I also investigate the relationship between individualism and pure creativity *outside of the career context*. While individualism is only weakly positively related to the Big Five creativity trait, *openness to experience*, as well as weakly negatively to the *agreeableness* trait, which negatively determines entrepreneurial longevity (Kritikos 2022), more individualist migrants choose to be significantly more involved in creative expression—either passively by attending

concerts and other cultural events or actively by creating artistic output themselves (i.e., by playing an instrument).

These findings on a direct effect of individualism on creativity and innovation behaviors are augmented by a mediation analysis to assess the relative importance of each innovation-conducive job-focused mechanism. Following Phelps (2013), I deconstruct the effect of individualism on individual productivity as measured by hourly wages to capture innovative activity comprehensively including incremental or grassroots innovation. Together, the career-related innovation choices explain 44 percent of the 7.9 percent wage premium associated with a one-standard-deviation increase in individualism. With a share of productivity explained that is similar to that of cognitive skills, selection into creative occupations is the most important innovation behavior in terms of explaining productivity. Since patents or other direct innovation output measures are not available in PIAAC, I turn to the PCT data to investigate the relationship between individualism and patenting behavior. The epidemiological framework has two main advantages compared to the previous cross-country evidence: First, it does not rely on country-level instrumental variables for identification but rather uses cultural variation within a destination country. Further, the data set from Miguélez and Fink (2013) offers less aggregate and more inventor-focused information based on yearly data on the number of international patents filed by all migrant inventors from a specific country in their destination country under the PCT system. The sample covers 118 destination countries and 68 origin countries and spans the years 1978 to 2012.[3] In an OLS specification with destination times year and continental fixed effects, the number of patents increases by 7.4 patents relative to an average of 8.3 when origin-country individualism increases by one standard deviation. A standard deviation in individualism roughly corresponds to the difference between Argentina (46), Germany (67), and the United States (91). Results are confirmed in Poisson count models and for the sample of single inventors.

Selection into migration that affects individualism and innovation, and unobserved origin-country heterogeneity are the two main endogeneity concerns regarding the epidemiological approach. Reassuringly, even if selection on individualism were present, it would most likely bias results downwards as one would expect the most individualist people from collectivist countries to select into migration and to innovate in the destination country.[4] The other key challenge is to disentangle the effect of individualism from other origin-country institutions and dimensions of culture. In particular, (cultural) risk preferences have been found to be correlated with innovation at the aggregate (Shane 1993) and entrepreneurship at the individual level (Levine and Rubinstein 2017; Kritikos 2022).

[3] The epidemiological approach is used in an aggregate version here since the data are available at the origin-destination-year level instead of the inventor level. Note that "destination country" refers to the location of residence of the migrant inventor—this is not necessarily the (only) country, in which the patent is filed, as the PCT is an international application system. The number of origin countries is restricted to those countries for which an individualism measure is available.

[4] In Hartinger et al. (2021), we show that migrant selection on individualism is not a concern in the PIAAC data.

The main results are robust to the inclusion of origin-country-level controls for other dimensions of culture, such as risk and time preferences, migration costs, and economic development as well as the introduction of origin-country fixed effects when within-origin-country variation in individualism is used. To abstract from the migration context, results are also confirmed in complementary specifications based on a person-level measure of individualism in the sample of natives as well as in region-level analyses.

Overall, results point towards an important role of individualism in multi-faceted dimensions of individual innovation production and creativity. These results contribute to several strands of literature. First and foremost, they add to our understanding of the economic effects of individualism. Individualism is currently remarkably present both in general society-wide debates (Dionne 2012) as well as economic research with its negative effects on aggregate pandemic response (Bazzi, Fiszbein, and Gebresilasse 2021) and redistribution (Bazzi, Fiszbein, and Gebresilasse 2020) and positive effects on human capital formation (Hartinger et al. 2021), democracy (Gorodnichenko and Roland 2021), and economic growth (Gorodnichenko and Roland 2011b, 2011a, 2012, 2017).

Importantly, is not the aim of the study to sharply distinguish between innovation and human capital. Innovation is strongly related to learning. Instead, innovation choices right *at the intersection* of creativity and learning seem to be particularly strongly affected by individualism. Biasi, Deming, and Moser (2021) provide a detailed overview of the link between education and innovation. They highlight the cumulative nature of both the education and the innovation process, with new ideas and new knowledge being added to the existing stock in the spirit of Scotchmer's (1991) knowledge production function.

Finally, I contribute to the general economic literature on personality traits and innovation by showing that individualism is more important for growth-relevant individual innovation choices than other dimensions of culture and personality commonly associated with innovation and highly studied in economics, such as cultural time and risk preferences (Bukowski and Rudnicki 2019; Hanushek et al. 2022; Sunde et al. 2022). The results presented in this study suggest that aspects of culture and personality—and, in particular, individualism—should be included in the discussion of innovative potential and the global flow of talent (Miguélez and Moreno 2013; Kerr et al. 2016; Andersson, Karadja, and Prawitz 2022), without, however, ranking or judging cultures or disregarding the disadvantageous effects of individualism.

The remainder of this paper is structured as follows: Section II describes the conceptual background and related literature. Section III discusses the main data sources and measures, and Section IV introduces the empirical strategies. Section V presents the results for individual innovation-conducive behaviors and is complemented by Section VII, which investigates the role of individualism in innovative productivity. Section VII summarizes the robustness checks followed by the concluding Section VIII.

II. Conceptual Background and Related Literature

A. *Individualism and Individual-Level Innovation*

Individualism describes a culture of *loose ties* between individuals (Hofstede 2001) based on the perception of the self as independent as opposed to interdependent (Markus and Kitayama 1991). The latter perception of the self corresponds to collectivism, the opposing pole of the individualism-collectivism scale developed by Hofstede (2001). Economists operationalize individualism by its many economically relevant connotations that are all deeply rooted in the independent self; such as an emphasis on freedom, autonomy, uniqueness, and achievement over harmony, conformity, and intra-group cohesion (Triandis 1995; Hofstede 2001). These connotations enter the individual innovation production function—which can be conceptualized as in parallel to the education production function (Hanushek 2020)—directly and indirectly: Directly through a distinct drive for achievement that makes innovation more desirable both from an extrinsic and intrinsic perspective; and indirectly, through mechanisms related to human capital accumulation and personality traits that affect a person's innovative potential and endowment.

Gorodnichenko and Roland (2017) highlight social status rewards that come with innovation as an extrinsic motivator. They show that these rewards result in higher aggregate innovation output in individualist societies. In this model, individualist societies award social status to those who stand out through innovation, entrepreneurship, and related personal accomplishments. The role of individualist societies in Western Europe and Anglo-Saxonian countries in breakthrough innovations and the rapid expansion of the technological frontier over the past centuries illustrates this argument (Gorodnichenko and Roland 2017). However, they fail to show how the status rewards translate into innovation-conducive behaviors at the individual level and *among the general population*. If, for instance, social status rewards are perceived as unattainable and reserved for a few innovation superstars, they may even be demotivating for the general population. Interestingly, the role of incentives is also reflected at the group level by Goncalo and Staw (2006) who show that more individualist groups perform better at creative tasks in the laboratory; but only when creativity is monetarily rewarded. Thus, it seems that rewards—be it monetary or through social status—are a powerful extrinsic force behind the individualist strive for innovation both at the aggregate and the individual level.

Significant intrinsic motivators associated with individualism co-exist with these extrinsic ones. Children from an individualist background learn at a very young age to discover and use their personal talents and gifts (Waterman 1984). Through perceiving themselves as independent and unique, individualist adults consequentially strive for *personal* achievement and success. Innovation and creativity are, arguably, ways of fulfilling the desire for both self-fulfillment and success at the individual level (Ivtzan 2008; Tsai 2021). Additionally, occupations related to entrepreneurship and innovation are

commonly characterized as offering high levels of freedom and independence, which the individualist strives for. After all, some of the questions from the Hofstede individualism index specifically capture the individualist desire for autonomy and freedom of choice of approach to the job. Thus, pursuing an innovation-focused career (through occupational selection or behavior on the job) potentially meets a lot of the individualist's key needs, such as self-fulfillment and independence—creating a significant intrinsic motivation to innovate at the individual level. Liñán, Moriano, and Jaén (2016) establish a link between individualism and entrepreneurial intentions at the individual level. They find that individuals in more individualist environments as well as those who are more individualist than their environment's average have higher entrepreneurial intentions. However, beyond intentions, there is a lack of evidence on the motivational effects of individualism on labor-market relevant innovation outcomes and real-life innovation choices at the individual level.

While motivational factors theoretically suggest a positive relationship between individualism and innovation, there are also endowment-related aspects that support the hypothesis. Individualism is commonly characterized as a *culture of life-long learning* (Hofstede 2001). To the extent that education enters positively in the individual innovation production function (Biasi, Deming, and Moser 2021), the higher human capital endowment of more individualist people would lead to a positive indirect effect of individualism on innovation.

While the education endowment channel is clear cut and well documented, a second endowment channel is less well understood: Individualism may be related to personality traits and cognition patterns that in turn matter for individual creativity and innovative potential. In fact, bringing together human capital and personality traits, Levine and Rubinstein (2017) show that successful Schumpeterian entrepreneurs are a combination of "smart and illicit", especially during adolescence. Their findings, thus, point towards an intertwined role of skills and personality in entrepreneurial success. Focusing on mental processes, Miron-Spektor, Erez, and Naveh (2011) highlight the role of cognitive style in team-based innovation. Similarly, Wu, Parker, and Jong (2014) find that a need for cognition is related to higher individual innovative performance, even when openness is kept constant. They argue that cognitive style underlies other important predictors of innovation, such as human capital and other personality traits.

Individualism is known to be associated with "analytical" rather than "holistic" cognition, which is common in collectivism (Masuda and Nisbett 2001; Nisbett et al. 2001). These distinct cognitive styles affect the way persons interpret situations, prioritize information, and even fall victim to specific cognitive biases (Choi and Nisbett 1998). The psychological evidence illustrates how deeply individualism affects the way we perceive and process the world around us. While differences in cognitive style are likely to affect individual creativity and innovation, this link is, unfortunately, understudied thus far. Most closely related to the arguments in this study are the results of a study in Kim and Markus (1999), who show that people from more individualist cultures prefer the more rare and

unique option in a choice of free pens. This subtle, low-stakes choice suggests that, indeed, individualist strive to stand out among their peers (rather than fit in) in everyday situations in a professional context, which could reflect, at least metaphorically, the desire to produce outstanding and unique ideas.

While further research in the area of cognition is needed, a well-established endowment factor of interest is creativity. Since creativity is hard to measure in survey data at the individual level, one may first turn towards personality traits that are related to creativity to capture the relationship between individualism and creativity. One such trait is *openness to experience*, one of the Big Five dimensions (Costa and McCrae 1992; Kritikos 2022). However, whether individualism is related to openness to experience as a creativity trait is still an open (and fundamentally empirical) question. At least for German panel data, only a weak relationship between individualism and openness as well as agreeableness is found in this study (see Table 3). Reassuringly, the evidence on individualism and creative output supports a Big Five-independent individualism effect on innovation (Goncalo and Staw 2006). Notably, Saad, Cleveland, and Ho (2015) provide experimental evidence for a nuanced relationship between individualism and creativity with individualists achieving greater quantity and collectivists greater quality of ideas. On the other hand, Zha et al. (2006) establish a direct link between individualism and creative potential in a sample of PhD students. Overall, it seems plausible that individualism influences creative potential—through and beyond openness to experience[5]—and, thus, indirectly affects individual innovation decisions from job selection to output generation.

While these different mechanisms related to motivation and endowment all point to a positive relationship between individualism and innovation at the person level, there is also one significant mechanism that allows for a negative relationship: The deficits in coordination and cooperation in more individualist contexts. Zheng (2010) highlights different aspects of social capital in the innovation process focusing on concepts such as tie strength (which would be related to collectivism) and trust (an aspect of individualism) as innovation-inducing. Andrews (2019) finds that informal communication channels matter for innovation. In the context of corporate culture, Charness and Grieco (2023) find that prosocial attitudes improve creative performance in group innovation tasks. This broad evidence immediately raises concerns about the ability of individualists to innovate, especially in team settings. After all, individualism strongly emphasizes *personal* achievements and responsibility over harmony and intra-group cohesion. However, this does not imply that individualists are unable to work together. They tend to have a more *transactional* rather than identity-relevant perspective on social interactions (Tiessen 1997), which guides their behavior towards others. Especially in professional settings, such a transactional perspective does not necessarily harm collaboration in the creative process, as

[5] According to Kritikos (2022), agreeableness is another important Big Five trait in the context of entrepreneurship. Unlike openness, it does not seem to affect entrepreneurial entry. Instead, agreeableness is negatively related to entrepreneurial survival, potentially through negotiation skills and the ability to manage unpleasant phases of business development (Caliendo, Fossen, and Kritikos 2014).

underlined by Goncalo and Staw (2006). However, doubts remain regarding the long-term effectiveness of individualist collaboration compared to the collectivist counterpart. Thus, even though many economic arguments predict a positive relationship between individualism and innovation in- as well as output at the individual level, this relationship remains fundamentally an empirical question.

B. *Dimensions of Innovation and Their Productivity Implications*

The aggregate evidence on individualism and innovation is strong. Correlational studies on the positive relationship between individualism and innovation indices (Rinne, Steel, and Fairweather 2013; Kapoor et al. 2021) are augmented by Gorodnichenko and Roland (2017) who provide evidence based on several instrumental variable approaches that exploit small genetic variations between populations that evolve in parallel to culture due to intergenerational transmission mechanisms. However, the individual-level behaviors and choices that underly these aggregate effects have largely remained opaque. For instance, a model of a stark innovation gap between few highly productive individualism-motivated superstar innovators and a discouraged remainder of the population would be consistent with the aggregate findings—but would have very different policy implications compared to a grassroots innovation social status return that applies throughout the population.

This paper provides a comprehensive micro foundation for the aggregate patterns by studying different dimensions of individualism-induced innovation at the individual level that may affect economic success through different channels. A look at diverse aspects of innovation helps uncover finer growth mechanisms through creative social capital, innovation-biased technical change, diffusion of knowledge, and agglomeration of talent. To connect the empirical evidence on individual innovativeness to the aggregate growth effects, this section discusses the mechanisms behind potential growth effects of each dimension of innovativeness studied in this paper.

In terms of innovation output, patents are arguably the classic measure, and their direct connection to economic success through innovation incentives has long been established (O'Donoghue and Zweimüller 2004; Mokyr 2009; Hall and Harhoff 2012). Individualism particularly rewards breakthrough (rather than incremental or process) innovations, which are traditionally more likely to get patented to secure intellectual property rights (Arundel 2001)—predicting a positive individualism effect on patenting behavior. At the same time, Phelps (2013) advocates for more inclusive measures of innovative activity, such as general productivity as captured by wages. He argues that such measures are better suited to capture grassroots innovation within the entire population and to understand the full *indigenous innovation* potential of a society. This is why the mediation analysis in Section VI.B focuses on wages as the outcome variable.

Regarding the underlying individual behaviors, which can be seen as inputs of an innovation production function, the implications for economic success are more subtle and may depend on the exact classification used to characterize occupations. First, several

classifications explicitly revolve around research occupations and other occupations that deal with complex problem solving. These occupations are often heavy in abstract tasks and may therefore benefit from task-biased technological change (Acemoglu and Autor 2011), leading to higher economic success at the individual and aggregate level. Piekkola (2020) even argues in favor of innovation-labor-biased technical change, where technology is pushed further by those in innovative occupations and, consequently, is biased in favor of those in such occupations.

For those innovation-relevant occupations that lean more towards creativity rather than problem-focused technical innovations—such as performing artists on the narrow side of the spectrum or Florida's (2002) creative occupations on the broad side of the spectrum—, the attraction and agglomeration of talent and creative capital may be a key factor for individualism-based economic success. On the one hand, Florida (2002) models the presence of creatives in a region or metropolitan area as a non-monetary amenity that attracts talent and makes the region (or country) more attractive for intellectuals, entrepreneurs, and innovators. On the other hand, creativity and intellectual output (even if not related to structural innovation or technical change) are arguably part of social capital (Putnam 1996, 2000) and a society's indigenous innovative potential (Phelps 2013, 2018). Thus, in addition to its effects on human capital (Hartinger et al. 2021), it is plausible that individualism also increases growth-relevant intangible socio-intellectual capital through the accumulation of creative and intellectual output, even when said output is not at the technological frontier. In fact, recent literature emphasizes the intertwined role of socio-cultural capital and human capital in innovation (Zheng 2010; Piekkola 2020). Based on a survey of organizations, Subramaniam and Youndt (2005) argue that both human capital and social capital in combination are required for radical innovation.

Beyond occupational selection, individualism may also affect day-to-day behavior on the job in a way that is innovation-conducive. Adding on-the-job behavior as another, more casual, dimension of innovation has two advantages: First, it allows for within-occupation comparisons of more or less innovative workers based on their individualism level. Second, casual innovation-conducive behavior can be found in a broad range of occupations—far beyond the classic innovative research occupations and more inclusive of small process innovations than patents. If individualism affects innovation within occupation for a broad range of occupations, this points towards an individualism effect on the broad innovative potential of a society in the spirit of Phelps (2013, 2018) rather than a superstar phenomenon limited to a small subpopulation. Ford (1996) models within-occupation differences in innovativeness as the result of a deliberate choice of a standard versus an innovative approach to one's occupation. Innovative behavior can be seen as a multifaceted process from problem recognition and idea generation to implementation, following Scott and Bruce (1994). In relation to the Ford (1996) model, Erez (2010) highlights the role of culture in job design and interpretation. She argues that people from different cultures craft (similar)

jobs in different ways, with employees from individualist cultures favoring freedom as opposed to low-empowerment and low-conflict settings.

To capture innovation-conducive behavior at work, I focus on active learning behavior, such as staying up to date and learning by doing. A learning-focused approach to the joy implies an active interest in gaining and spreading knowledge. These three learning behaviors are directly related to the diffusion of knowledge and, in occupations where it is possible, the adoption of new technologies. Diffusion and technology adoption are core elements of the innovation process and highly growth-relevant (Schumpeter 1911, 1942; Acemoglu and Autor 2011; Acemoglu, Gancia, and Zilibotti 2012; Sampson 2023).

Taken together, these individual innovation choices help clarify the microeconomic mechanisms behind the large growth effects of individualism through aggregate innovation despite potential institutional weaknesses.

III. Data and Measurement

This section presents several primary data sources to measure the various dimensions of innovation as well as individualism. One main prerequisite is that the data are international as to ensure that the results do not depend on one particular cultural context. For this reason, international patent data and education and labor-market data are the focus of the study. Only in the case of creativity traits, the analysis is only based on German data, where Big Five measures are readily available for a meaningful number of migrants. Descriptive statistics of important variables are summarized in Table A1 for all samples. A detailed description of the German Socioeconomic Panel data set as well as control variables from external data sources is relegated to Appendix Section B.

A. *PIAAC*

The analyses of occupational selection and approach to the job are based on data from PIAAC, the OECD's Programme for the International Assessment of Adult Competencies (see OECD 2013 for details). At its core, PIAAC provides internationally comparable measures of cognitive skills for adults aged 16 to 65 years.[6] With a total sample size of approximately 243,000 individual-level observations, samples are drawn representatively in each country and consist of at least 5,000 adults per country. In addition to the cognitive skill measures in the three domains of numeracy (i.e., the skill to access, use, interpret, and communicate mathematical information and ideas to engage in and manage the mathematical demands of a range of situations in adult life), literacy, and problem solving in technology-rich environments

[6] 38 countries participated in PIAAC in rounds one to three from 2012 to 2018. Of these countries, Australia, Belgium (Flanders), Chile, Cyprus, the Czech Republic, Denmark, Ecuador, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Lithuania, the Netherlands, Norway, New Zealand, Mexico, Peru, Poland, Russia, Singapore, the Slovak Republic, Slovenia, Spain, Sweden, Turkey, the United Kingdom (England and Northern Ireland), and the United States are used in the person-level individualism analysis for natives. The remaining countries are excluded due to missing information, for instance in the occupational variables. In the epidemiological approach, Australia, Ecuador, Ireland, Italy, New Zealand, Norway, Sweden, the United Kingdom, and the United States are dropped due to missing country-of-birth information. Indonesia retracted their data entirely; they are therefore unavailable.

(ICT skills)—all measured on a 500-point scale and with a focus of capturing labor-market relevant competencies—, PIAAC collects extensive education and labor-market information as well as personal learning behaviors in a thorough background questionnaire. The present study draws heavily on this background questionnaire for information on occupation, wages,[7] and learning behaviors on the job between and within occupation.

Information on current occupation is available up to the four-digit ISCO-08 level in the main estimation sample. For each observation, the most detailed available ISCO-08 information is used in the occupational classifications. I use several binary occupational classifications—indicators equal to 1 if a person works in an innovative occupation, and 0 otherwise—to determine the effect of individualism on selection into innovation-conducive occupations. The broadest classification follows the operationalization of Florida's (2002) definition of creative occupations comprised of the creative core and other creative professionals developed in Cruz and Teixeira (2014). The creative core covers STEM, IT and other scientific occupations, education occupations, as well as arts, design, entertainment, sports, and media occupations (the latter occupations are referred to as *Bohemians*). Creative professionals include business, legal, and management occupations, healthcare and technical occupations, and higher positions in sales and sales management. Creative occupations as the broadest concept of innovative jobs cover 43 percent of the main estimation sample. Two complementary classifications zoom in on classic-creative occupations by focusing only on the *Bohemians* (3 percent of the main sample) and, even more narrowly, only on *performing artists* (1 percent) to investigate if the individualism effect on occupational choice operates mainly through high-paying structurally innovation-focused occupations or if more creative-innovative occupations are also affected.

Finally, in line with the previous literature on individualism and research occupations, I use Gorodnichenko and Roland's (2017) concept of research occupations as operationalized for ISCO codes in Hartinger et al. (2021). Extending previous evidence by looking at ambitious self-employment, I investigate whether more individualist people are more likely to work in a research occupation conditional on being self-employed. Self-employment is measured via an indicator that takes the value of 1 for currently self-employed individuals and 0 for salary-employed individual. The three measures for knowledge diffusion at work, *learning by doing*, *staying up to date*, and *learning from co-workers*, capture how often the respondent reports engaging in the respective behavior. They are measured on a five-point scale ranging from "never" over "less than once a month", "less than once a week but at least once per month", and "at least once a week but not every day" to "every day". The scales are coded so that higher values indicate more frequent behaviors and standardized to a mean of 0 and a standard deviation of 1 in the full international sample.

[7] The PIAAC Public Use File reports gross hourly wages for Hungary, Singapore, Sweden, Turkey, and the United States only in the form of worker's decile rank in the country-specific wage distribution. Values are imputed using OECD information. I trim the bottom and top 1 percent of the wage distribution to mitigate the impact of outliers. Peru does not provide wage information.

In the epidemiological approach, information on the migration status and country of origin of first-generation migrants needs to be available as well as information on employment and occupation. This leaves a sample of more than 4,500 first-generation migrants from the 67 countries for which a Hofstede individualism score is available. They reside in the following 25 destination countries where they participated in PIAAC: Belgium, Chile, Cyprus, the Czech Republic, Germany, Denmark, France, the United Kingdom, Greece, Hungary, Israel, Japan, Kazakhstan, Korea, Lithuania, Mexico, the Netherlands, Peru, Poland, the Russian Federation, Singapore, the Slovak Republic, Slovenia, Spain, and Turkey.[8]

Since the person-level individualism approach is not limited to countries for which a Hofstede individualism measure is available, the sample of first-generation migrants is substantially larger in this approach—spanning more than 6,000 migrants from 170 origins. Additionally, this approach estimates the relationship between individualism and innovation in the sample of close to 100,000 natives to abstract from the migration context of the other analyses. To balance differences in sample size between the different destination countries, all PIAAC-based regressions are weighted in all individual-level analyses, such that each destination country receives the same weight.

The regional analysis is based on the following 25 countries that each have more than one region from the OECD's TL2 classification of large regions represented in the data set: Chile, the Czech Republic, Denmark, Ecuador, France, Germany, Greece, Hungary, Ireland, Israel, Japan, Kazakhstan, Korea, Lithuania, Mexico, the Netherlands, New Zealand, Peru, Poland, the Russian Federation, the Slovak Republic, Slovenia, Spain, Sweden, and the United Kingdom. For Ecuador, Estonia, Lithuania, New Zealand, and Peru, OECD patent data is not available for more than one TL2 region, which is why they are excluded from the patent analysis.[9] The main regional sample consists of 270 regions, covering 62 percent of the total 433 TL2 regions.

B. *PCT Patent Data*

International patent data is based on the Patent Cooperation Treaty (PCT) and is taken from Miguélez and Fink (2013) who explain the data set in detail. The PCT is administered by the World Intellectual Property Organization and is designed to simplify the process of obtaining international patent protection in lieu of an international patent system. Miguélez and Fink (2013) argue that the PCT will likely cover the most valuable and most highly used patents for which seeking international patent protection is profitable. Their database covers migrant inventors for a large number of years (1978 to 2012)[10] and 241 destination

[8] Upon imposing more rigorous sample restrictions for a robustness check (at least 100 first-generation migrants from at least 10 different Hofstede countries), the following countries drop out: the Czech Republic, Japan, Kazakhstan, Korea, Lithuania, Mexico, Peru, Poland, the Russian Federation, the Slovak Republic, and Turkey. Results are robust, see Appendix Table E1 and Table E2.

[9] Additionally, there are missing patent values for some regions in other countries, which reduces sample size to 196 regions.

[10] Due to changes in the reporting requirements for PCT patent applications after 2012, the data cannot be extended beyond that year. See Miguélez and Fink (2013) for details.

as well as sending countries / territories—as of 2012, 146 countries participated in the PCT, including the world's highest patenting countries (Miguélez and Fink 2013). The data are inventor-focused in the sense that they provide information on first-generation migrant (applicant-)inventors and their origin as well as destination country. At the same time, the data are aggregate in the sense that the unit of observation is not the single inventor or patent but rather the aggregate count of patents filed by all inventors from one specific country in one specific destination country in a year. One inventor could, in principle, be counted multiple times in the same year. The data, thus, reflect the yearly innovative activities of migrants by origin-destination country pair without making claims regarding the distribution of this creative potential among migrants from the same origin. In the data, the year information refers to the priority year—the year a patent is first filed anywhere.

The database allows to look at single-inventor patents separately, which is relevant in the context of individualism. Due to the large number of country pairs in the database, some sample restrictions are imposed to estimate the relationship between individualism and patenting for a meaningful sample that does not contain excessive zeros: Countries as well as origin-destination pairs for which the PCT patent count is always zero are omitted. Results are, however, robust to removing any sample constraints as Appendix Table E6 confirms. The final estimation sample covers 118 destination countries and the 68 origin countries for which a Hofstede individualism value is available.

C. *Individualism*

Individualism has been conceptualized and popularized by Hofstede (2001) as one of five main cultural dimensions. Thus, it is not surprising that the Hofstede individualism index is the most widely used individualism measure at the country level. To this day, the index is mainly based on international IBM employee surveys from the late 1960s and early 1970, although several replication studies allowed for the addition of more countries afterwards. It is currently available for close to 70 distinct countries and is measured on a scale from 0 to 100. Six items from the IBM survey are commonly referred to as the core individualism items even though the original index is based on a factor analysis on 14 items: The index loads positively on employees' preferences for challenging work, freedom in choosing their own approach to the job, and free time for their personal life. The index loads negatively on a number of work environment items, such as physical working conditions.

Since the index is fundamentally based on a workplace survey, there may be concerns regarding the purity of this individualism measure especially in relation to the innovation and career focus of this study. Reassuringly, individualism is generally known to be very robust with respect to measurement (Oyserman, Coon, and Kemmelmeier 2002). Alternative aggregate individualism-collectivism measures focus on linguistic characteristics (Kashima and Kashima 1998) or family norms (Gelfand et al. 2004; House 2004). Schwartz' (1994) popular *autonomy* and *embeddedness* dimensions are also directly

related to individualism-collectivism. All main results of this study are robust to using alternative country-level individualism-collectivism measures.

The person-level individualism index used in this study combines two of the many robust ways of measuring individualism at the person level (Oyserman, Coon, and Kemmelmeier 2002): Individualism is measured through the individualist core features of challenge-seeking, analytic curiosity, and lifelong learning (Hofstede 2001) as well as through generalized trust (Guiso, Sapienza, and Zingales 2006; Tabellini 2008). Lifelong learning is captured through two items where respondents indicate to which extent they enjoy learning new things in general, and whether they enjoy getting to the bottom of difficult things. Additionally, analytic cognition as described in Nisbett et al. (2001) is measured through one item that captures to which extent respondents enjoy figuring out how different ideas fit together.[11] Finally, this index makes use of (high) generalized trust as a well-known characteristic of individualism (Gorodnichenko and Roland 2012). Guiso, Sapienza, and Zingales (2006) show that trust matters for entrepreneurship. In PIAAC, generalized trust is measured via two items: Participants indicate to which extend they generally trust people, and to which extend they believe other people generally take advantage of them. While the generalized trust measure is, arguably, free from reverse causality concerns in the workplace context, it only captures one very particular aspect of individualism rather than the whole concept. When combining generalized trust and the other private-life-related items, the resulting index meets the acceptability criteria for internal reliability (Cronbach's alpha = 0.61) and is meaningfully correlated with the Hofstede index: Appendix Figure A1 shows the country-level correlation with the Hofstede index, the correlation coefficient is 0.52. These validation exercises demonstrate that the person-level individualism index is a valuable addition to the set of individualism measures. It will be used at the individual and region level in the analysis.

IV. Empirical Set-Up

As is common with deep aspects of personality and identity, estimating a causal effect of individualism on economic outcomes is challenging. Since experimental data that randomly vary a person's individualism level are neither available nor ethically desirable, this paper combines several data sources covering different aspects of innovation and relies on multiple complementary estimation strategies.

A. *The Epidemiological Approach*

The most trusted approach for uncovering economic implications of culture is the so-called *epidemiological* approach. In its essence, this empirical strategy compares (first- and

[11]These three items are also part of the broad individualism index developed and validated in Katharina Hartinger et al. (2021). The remaining items of said broad individualism index are work-related and are omitted from the main index in this study due to reverse causality concerns with respect to the career outcomes. Table E3 shows that results are robust when the broad individualism index from Hartinger et al. (2021) is used.

or second-generation) migrants from *different* cultural backgrounds within the *same* destination country (Fernández 2007; Fernández and Fogli 2009; Figlio et al. 2019). The institutional and economic environment of the destination country is held constant while culture varies by the migrants' origin country. Thus, the epidemiological approach eliminates concerns regarding omitted factors related to the current environment of migrants, such as labor market quality, intellectual property rights or innovation opportunities. An important assumption of the approach lies in the stability of culture across space and time that has been well documented in the literature with an emphasis on labor-supply-relevant attitudes (Fernández 2007; Alesina, Giuliano, and Nunn 2013; Alesina and Giuliano 2015; Bredtmann and Otten 2022).

The epidemiological approach is used at two different levels of aggregation in this study. To assess the implications of individualism for broader measures of innovativeness, individual-level data are available, and the classic epidemiological approach with its individual-level estimation can be used. Identification is based on a comparison of the innovativeness of first-generation migrants (within the same destination country) who differ with respect to their origin-country culture as formalized in equation (1).[12]

$$INNO_{ido} = \beta_0 + \beta_1 \overline{IDV_o} + \boldsymbol{X}'_{ido}\boldsymbol{\gamma} + \mu_d + c_o + u_{ido}. \quad (1)$$

The respective innovative behavior—occupation, creativity, and behavior on the job—of first-generation migrant i in destination country d from origin country o, $INNO_{ido}$, is regressed on the origin-country individualism measure, $\beta_1 \overline{IDV_o}$, and individual-level controls, specifically gender, age and age squared as well as (destination-specific) origin-country controls $\boldsymbol{X}'_{ido}\boldsymbol{\gamma}$. A key component of the epidemiological approach are destination country fixed effects.[13] Since individualism varies at the origin country level, origin country fixed effects cannot be included. Instead, I include origin continent fixed effects c_o to capture relevant geographical bunching in individualism, such as systematic differences between Western and Asian cultures. Typically, the epidemiological approach for first-generation migrants additionally includes year of migration fixed effects (interacted with the destination country fixed effects) to account for migration waves. However, due to the rather low number of migrants per migration year per country working in the same industry, which counteracts the key concept of the epidemiological approach, they are relegated to Appendix Table E1 and Table E2 in this study. Results remain unaffected by their inclusion. Standard errors are clustered at the origin-country level.

The analysis of the relationship between individualism and patents as a key innovation output indicator is based on an aggregate version of the epidemiological approach. Here,

[12] To highlight that equation (1) and (2) use the same underlying epidemiological structure, coefficient labels (such as β) and variable labels are repeated for expositional reasons even though their estimates are naturally not identical in both regressions.

[13] Since the analyses based on the SOEP only use one destination country (Germany), destination-country fixed effects are not included in these specifications.

instead of looking at single migrants, the total number of patents (per year per destination country) generated by *all* (first-generation) migrants from a specific origin country are considered and compared between culturally different origin countries as outlined in equation (2). The outcome is, thus, not measured at the level of the single migrant but at the level of all migrants from the same origin country (in a destination country in a year). This aggregate epidemiological approach is conceptually equivalent to the individual-level approach and chosen for data availability reasons. Since the patent data in Miguélez and Fink (2013) are count data, logit, negative binomial, and (mainly) Poisson estimators will be used in addition to OLS to estimate equation (2).

$$PAT_{dot} = \beta_0 + \beta_1 \overline{IDV_o} + \boldsymbol{X}'_{ot}\boldsymbol{\gamma} + \mu_d \times \mu_t + c_o + u_{dot}. \quad (2)$$

I regress the aggregate count of patents generated in destination country *d* by all migrants from origin country *o* in year t, PAT_{dot}, on the Hofstede individualism score of the respective origin country, $\overline{IDV_o}$. Equation (2) contains the full set of interactions between destination country and year fixed effects, $\mu_d \times \mu_t$, ensuring that only migrants who generate patents in the same destination country and the same year are compared. This accounts for country differences and (country-specific) time trends in patenting. Characteristically, origin-continent fixed effects, c_o, also appear in this equation. Standard errors are, again, clustered at the origin country level.

With respect to causal identification, the key assumption of both the classic and aggregate epidemiological approach is that migrants *only* bring their culture with them from the origin country. This is a very strong assumption especially for first-generation migrants, since any cultural, economic, and institutional characteristics of the origin country that affected the migrants' upbringing could bias the results if they are correlated with origin-country individualism and migrants' innovativeness. However, further considerations are necessary to assess the extent of this concern: Some origin-country characteristics can be controlled for explicitly, i.e., other dimensions of culture. So far, only two of the many dimensions of culture have been found to be of first-order economic importance.[14] They are individualism (and the sub-concept of trust) and long-term orientation. In addition, uncertainty avoidance (cultural risk preferences) can be expected to matter in the innovation context (see Section II.A). Controlling for established measures of these cultural dimensions is possible in the epidemiological approach.

Non-cultural origin-country characteristics need to be added to the epidemiological approach with caution. For instance, Gorodnichenko and Roland (2011b, 2012) show that individualism is a key cultural determinant of long-run economic growth. If GDP is an outcome of individualism, controlling for GDP in the epidemiological approach creates a

[14] Additionally, specific cultural norms have been found to matter for *specific* economic contexts (see, for example, Alesina, Giuliano, and Nunn (2013) for an economic investigation of cultural gender norms in the labor market).

bad control problem—especially since economic success, innovation, and individualism are intertwined. Nonetheless, the relationship between individualism and innovation net of origin-country wealth is interesting in itself, especially in the case of the aggregate epidemiological approach.

Since the epidemiological approach relies on migrants for identification, additional concerns regarding migrant selection emerge. This issue may be particularly severe in the context of innovation since mobility is well documented among innovators and entrepreneurs in the context of global talent flows (Miguélez and Moreno 2013; Kerr et al. 2016). The cross-sectional nature of the PIAAC data and the aggregate nature of the Miguélez and Fink (2013) data do not allow for a systematic evaluation of migrant selection that would eliminate all such concerns. However, selection is only relevant to the validity of the results if migrants are selected on individualism itself or on a third factor that is related to both individualism and innovation. In the entrepreneurial context, it certainly seems plausible that particularly *individualist* persons in collectivist societies may choose to migrate to pursue innovation. However, this behavior observed in a very specific group of migrants does not lead to systematic selection on individualism overall, as Hartinger et al. (2021) show. When estimating the relationship between individualism and innovation, this type of selection is not a first-order concern as it would result in *understating* the true individualism effect in the estimation: These highly innovative migrants would systematically be assigned an individualism value that is substantially lower than their true individualism level, leading to a *downward* bias in the results.

B. *Person-Level and Regional Individualism Approaches*

Overall, the three main drawbacks of the epidemiological approach—limited sample size, origin-country confounders, and migrant selection—call for a second, complementary approach based on a different source of variation in individualism. Turning from a country-level measure of individualism to a *person-level* measure and the *regional* aggregate of the respective measure offers exactly that.

At the individual level, the personal measure allows for two valuable analyses: First, it enables the use of origin-country fixed effects since individualism is now no longer measured at the origin-country level. Thus, only first-generation migrants who migrated from the same origin country to the same destination country (in the same year) but differ with respect to their personal individualism score (through differences in character or assimilation) are compared. This specification eliminates concerns regarding omitted origin-country characteristics. Second, it allows for a comparison of natives who simply differ with respect to their personal individualism level irrespective of any migration context. An analysis based on natives naturally mitigates any endogeneity issues related to migrant selection and adds to the external validity of the results.

At the regional level, the regionally aggregated person-level individualism measure allows to compare culturally different regions within the same country. It is comparable to

the epidemiological approach in the sense that is also exploits variation in individualism within a country. However, the regional analysis provides a way of exploiting within-country variation that is not plagued by omitted variables at the individual level.

In practice, the person-level individualism approach estimates equation (1) with (only) destination-country fixed effects for natives. For the respective migrant specifications, the full interaction of origin-country, destination-country, and year-of-migration fixed effects is included. The regional approach estimates the regression of regional innovation on regional individualism and country fixed effects. Overall, the empirical strategy in this paper relies on a combination of different methods and sources of variation in individualism to paint a consistent picture of implications of individualism for innovation in the absence of truly exogenous variation.

V. Individualism and Innovation Behaviors

This section documents the relationship between individualism and innovation behaviors. These behaviors include selection into innovative and creative occupations, knowledge diffusion on the job through learning and keeping up to date, and creativity as captured by traits and leisure behaviors. Since these facets of innovativeness have different implications for economic growth and different policy implications, it is important to analyze them separately. Taken together, results point towards strong returns to individualism with respect to innovativeness, which then translate into productivity premia as shown in the subsequent section.

A. *Occupational Selection*

Occupational selection is arguably a key measure of innovativeness as selecting an innovation-conducive profession is a very structured way of engaging in innovation. Stiglitz (2009) emphasizes the role of innovative professions and structural innovation conducted by R&D departments and research institutes in the innovative potential of a country. As far as selection into innovative occupations is concerned, previous research has focused only on selection into research-focused occupations (Gorodnichenko and Roland 2017; Hartinger et al. 2021). Column (4) of Table 1 briefly confirms these results for PIAAC rounds 1 to 3. Those migrants with a one-standard-deviation higher individualism score are 3 percentage points more likely to work in a research occupation.

However, since research occupations only account for 11 percent of jobs in the estimation sample (and only 7 percent in the full OECD PIAAC sample), alternative classifications of occupations into more or less innovation-conducive jobs allow for a more complete picture of the role of individualism in occupational selection and structural innovation: The broadest conceptualization of innovation-conducive jobs, creative occupations following Florida (2002), accounts for 43 percent of occupations in the sample. Individualism and has a positive and highly significant impact on selection into these occupations. If individualism increases by one standard deviation—corresponding roughly to the difference between

Argentina (with a score of 46 on the Hofstede scale) and Germany (67)—, the probability of working in a creative occupation increases by 8 percentage points or 19 percent of the sample share. This suggests that individualism impacts selection into a broad range of innovation-conducive occupations held by almost half of the sample. Thus, the returns to individualism do not seem to be absorbed solely by an elite of researchers and entrepreneurs but by a broader share of the population ranging from IT professionals and educators to media professionals and certain medical personnel.

To show that the results for creative occupations are not simply driven by researchers who appear in both categorizations discussed above, I zoom in on the *Bohemians* in Florida's (2002) framework. This classification focuses on creative occupations in media, performing arts, design, and communication. It only makes up 3 percent of occupations in the sample. Yet, the individualism coefficient in Column (2) is once again positive, large, and highly significant at 0.019—a one standard deviation increase in individualism raises the probability of being a Bohemian by 63 percent relative to baseline. Selection into these occupations, which combine classic creativity with innovativeness, is, thus, also positively affected by individualism.

Diving even deeper into creative occupations, let us look at selection into truly artistic occupations. Only 1 percent of the sample holds a job in the performing arts, making this by far the narrowest classification of creative-innovative jobs. However, it is a particularly interesting outcome as (contrary to, for instance, research occupations), artistry is often associated with a high level of creativity in combination with low monetary rewards. Despite the limitations of this outcome (i.e., the low share of artists in the population, especially among migrants), considering artistry as an outcome allows to disentangle a financial and a creativity-driven motive behind occupational choice. Indeed, more individualist people are more likely to become artists. The positive relationship between individualism and the propensity to work in an artistic occupation is strong and highly significant: A one standard deviation increase in individualism raises the probability of working in the performing arts by 0.7 percentage points or 70 percent relative to baseline.

Table 1. Individualism and Selection into Creative-Innovative Occupations

	Full Sample					Self-employed
	Creative Occupation	Bohemian	Artist	Research	Self-employed	Research
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.080***	0.019***	0.007***	0.030***	0.014*	0.043**
	(0.020)	(0.004)	(0.002)	(0.006)	(0.007)	(0.016)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.43	0.03	0.01	0.11	0.14	0.12
R-squared	0.12	0.04	0.02	0.04	0.05	0.10
Origins	67	67	67	67	67	57
Observations	4,627	4,627	4,627	4,627	4,627	623

Notes: The table shows the results for the outcome indicated in the column header in the sample of first-generation migrants. The results are based on the full sample (Columns (1) to (5)) and the sample of self-employed migrants (Column (6)). Observations are weighted, giving each destination country the same weight. *Creative class* and *Bohemian:* dummy variables equal to 1 if the respondent works in an occupation that matches Cruz and Teixeira's (2014) operationalization of Florida's (2002) respective concepts, and equal to 0 if the respondent works in any other occupation. *Artist:* a dummy variable equal to 1 if the respondent works in an active artistic profession, and equal to 0 if the respondent works in any other occupation. *Research occupation:* a dummy variable equal to 1 if the respondent works in one of the following two-digit ISCO occupations: 21 (science and engineering professionals), 25 (information and communications technology professionals), 26 (legal, social and cultural professionals), and equal to 0 if the respondent works in any other occupation. *Self-employed:* dummy variable equal to 1 if respondent is self-employed and 0 if respondent is employed. Individualism refers to Hofstede's index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Covariates*: age, age squared and a gender dummy. *Fixed effects:* destination country and continent of origin country. Standard errors clustered at the origin-country level reported in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PIAAC, Hofstede (2001).

Another first-order outcome of occupational selection is entrepreneurship: With their independence-focused mindset, individualist persons seem predisposed to be self-employed. However, the relationship between individualism and self-employment is less straightforward than expected, which is highlighted by the inconclusive previous literature where results seem to dependent strongly on the cultural context (Hofstede et al. 2004; Liñán, Moriano, and Jaén 2016; Nikolaev, Boudreaux, and Palich 2018; Barrios, Hochberg, and Macciocchi 2021; Mostaghel, Oghazi, and Patel 2023). Individualism is positively and significantly related to self-employment in the sample covering countries from all three PIAAC rounds for this study with a 1.4 percentage point increase in the probability of being self-employed for an individualism increase of a standard deviation. This amounts to a 10 percent increase relative to the 14 percent baseline. However, this result is weaker than the other occupational selection measures as it is only significant at the 10 percent level and turns insignificant in a number of robustness checks described below. An explanation for the weak result may lie in the various necessity-based motives for self-employment among migrants that are not related to innovation-focused entrepreneurship at all. Generally, Levine and Rubinstein (2017) argue that the simple self-employment measure is not a good proxy for Schumpeterian entrepreneurship. Instead, they measure disruptive

entrepreneurship by looking at those self-employed who choose an incorporated law form for their enterprise since it is associated with better protection against high risks. While such information is not available in PIAAC, individualism does affect the probability of being active in the research sector *within the group of entrepreneurs*: Although the sample size is small with 623 self-employed first-generation migrants, a one standard-deviation increase in individualism raises the probability of being classified as a researcher by 4.3 percentage points conditional on being self-employed. The coefficient is significant at the 5 percent level. Arguably, self-employment within innovative occupations can be considered as ambitious, Schumpeterian (1911, 1942) entrepreneurship.

Nonetheless, as evident in Appendix D.1 and E.1, the unconditional self-employment effects are much less robust than the other dimensions of occupational selection. There, the main results are remarkably robust to the inclusion of controls for migration costs and migrant selection in Table D1 in the form of educational selection, geographic distance, contiguity, linguistic proximity, genetic distance, and inequality distance at the origin-destination-pair level, and origin-country controls as well as controls for long-term orientation and uncertainty avoidance as key dimensions of culture in Table D3. All results except for self-employment are also significant when sample restrictions regarding the number of migrants as well as year-of-migration-specific destination country fixed effects are introduced in Table E1. The main results are also robust to using alternative individualism-collectivism measures although these results are omitted due to the large number of measure-outcome permutations. Overall, even though the predictive power of the models is low—arguably due to the omission of several factors that determine occupational choice—the results in Table 1 support the hypothesis that individualism systematically and strongly positively affects innovation through explicit occupational choice. While the role of individualism in self-employment is less robust, individualism clearly matters for self-selection into creative-innovative occupations in their various broad and narrow conceptualizations, highlighting its role as a cultural driving force behind important labor-market decisions for the individual and structural innovative potential.

B. *Knowledge Diffusion on the Job*

Although the previous section has shown substantial selection into innovative occupations due to individualism, it would be an oversimplification to only focus on job selection as a particularly well structured and measurable dimension of innovation. After all, at the individual level, selection into an innovative occupation is merely the beginning of the innovative process, which then happens at work. Thus, Table 2 summarizes how individualism affects behavior *on the job* as a separate dimension of innovation. Three specific behaviors are used to measure an innovation-conducive approach to the job in the spirit of Ford (1996): Learning by doing, keeping up to date, and learning from coworkers. All three behaviors are related to the diffusion of knowledge and the ability to adopt new technologies and incorporate new knowledge into the employee's workflow. Although

difficult to measure, technology diffusion and adoption are growth-relevant as an integral part of the innovation process (Eaton and Kortum 1999; Sampson 2023). Arguably, learning behaviors are among the most direct measures of the diffusion of knowledge at the workplace. By engaging in these three innovation-conducive behaviors, employees push their know-how and skill set towards the technological frontier of their occupation, which creates an ideal breeding ground for further innovation. Innovative behavior at work may also be strongly related to process innovations and smaller improvements (Phelps 2013, 2018) as well as innovations in small firms, which are often protected via secrecy rather than patents (Arundel 2001).

The three learning behaviors of interest are very general and can, in principle be observed in many different jobs. Since some occupations are, as established above, generally more innovation-focused, this immediately leads to the key question of distinguishing the effect of individualism on innovative behavior *between* and *within* occupations. Columns (1)-(3) show the results for the between-occupation specifications for all three innovation-conducive behaviors while Columns (4)-(6) present the within-occupation results. Individualism is significantly related to learning on the job between and within occupation, even though the within-occupation results are less precisely estimated due to the variation taken away by the occupation fixed effects.

Table 2. Individualism and Knowledge Diffusion on the Job

	Between-occupation			Within-occupation		
	Keeping up to date	Learning by doing	Learning from coworkers	Keeping up to date	Learning by doing	Learning from coworkers
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.106**	0.086***	0.082***	0.058*	0.034*	0.032**
	(0.041)	(0.027)	(0.022)	(0.029)	(0.020)	(0.014)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
2-Digit Occupation				Yes	Yes	Yes
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.04	0.04	0.05	0.14	0.10	0.13
Origins	67	67	67	67	67	67
Observations	4,250	4,250	4,250	4,250	4,250	4,250

Notes: The table shows the results for the learning behaviors indicated in the column header in the sample of first-generation migrants. Results in Columns (4)-(6) isolate within-occupation variation in behavior by including two-digit ISCO fixed effects. Observations are weighted, giving each destination country the same weight. Keeping up to date, learning by doing, and learning from coworkers measure the self-reported frequency of the respective behavior at work on a five-point Likert scale. They are standardized to a mean of 0 and a standard deviation of 1 in the full international sample. Individualism refers to Hofstede's index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Covariates*: age, age squared, and a gender dummy. *Fixed effects:* destination country and continent of origin country. Standard errors clustered at the origin-country level reported in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: PIAAC, Hofstede (2001).

The between-occupation results are larger in size, re-emphasizing the role of occupational selection in the individual innovative capacity. For a one-standard-deviation increase in individualism, learning on the job increases by 8 to 11 percent of a standard deviation in the between-occupation model. Within occupation, returns to individualism range from 3 to 6 percent of a standard deviation. Although differences in effect size should not be over-interpreted due to the sample size, the effect seems to be strongest for keeping up to date: A one-standard-deviation increase in individualism raises the frequency of keeping up to date at work by 11 percent of a standard deviation between occupations and by 6 percent within-occupation. The coefficients appear moderate in size, but are economically significant: In the between-occupation specification, the coefficient on keeping up to date for a one-standard-deviation increase in individualism amounts to 150 percent of the difference between the average accountant and the average engineer in the PIAAC sample (natives and migrants).[15] It needs to be noted that these behaviors are entirely self-assessed, and further research should ideally include more objective measures of behavior and success at work to mitigate potential cultural differences in responding behavior. The robustness checks for the innovation-conducive learning behaviors follow the same structure as those for occupational selection outlined in the previous section, including the use of alternative individualism measures. Table D2 and Table D4 account for migration costs and origin-country characteristics. In both tables, the between-occupation results remain significant whereas the within-occupation results are somewhat less robust but confirm the direction of the effect. While this could be due to lack of variation after the introduction of many controls, it also re-emphasizes the importance of career choice in the innovative process. In the specification checks in Table E2, all coefficients remain significant and comparable if not larger in size than the main results. Despite the focus on between-occupation differences in innovation-conducive behavior, the results generally support the prediction that individualism has positive implications not only for selection into innovative occupations but also for subsequent behaviors at work that are innovation-enhancing by being tied to technology adoption and the diffusion of knowledge.

C. *Creativity*

Based on the classic epidemiological approach in the German SOEP data, Table 3 establishes the relationship between individualism and creativity as well as creative expression. Creativity is arguably a key input in the individual innovation production function. In the realm of deep personality traits, creativity is often operationalized as the "openness to experience" dimension of the Big Five traits: Openness to experience captures an interest in self-expression, culture (in the *les belles arts* rather than the *Hofstede* meaning of the word), and exploration (Costa and McCrae 1992). Kritikos (2022) surveys the

[15] For the other two behaviors, a one-standard-deviation increase in individualism closes 60 percent (*learning by doing*) and 45 percent (*learning from coworkers)* of the accountant-engineer gap. Further underlining the economic significance of the results, effect sizes for all three learning behaviors are roughly equal to the gender gap in these same behaviors.

literature on personality traits and entrepreneurship from an economic perspective and emphasizes the role of *openness to experience* out of the Big Five personality traits. Clearly, openness is empirically very strongly related to innovativeness (Zhao and Seibert 2006) and selection into entrepreneurship (Caliendo, Fossen, and Kritikos 2014; Kerr, Kerr, and Dalton 2019).

Column (1) of Table 3 shows that first-generation migrants in Germany that are from more individualist cultural backgrounds score slightly higher on the openness dimension. If individualism increases by one standard deviation, a person's average openness score increases by 0.046 points. The coefficient is marginally significant and positive but weak in size relative to the 4.69-point average score. For comparison, this corresponds to slightly less than a quarter of the gender gap in openness. Out of the Big Five, individualism is most significantly related to agreeableness, where a one-standard-deviation increase in individualism is associated with a decrease in average agreeableness by a significant 0.038 points. While this coefficient is also small, it is noteworthy that agreeableness has been found to affect the long-term success of entrepreneurs (Caliendo, Fossen, and Kritikos 2014). Since culture and personality traits tend to be constructed and measured separately from one another in psychology, it is reassuring to see that while individualism is weakly positively linked to creativity in the German sample, it acts as a separate concept of self that is not simply a representation of one or several Big Five traits.

Table 3. Individualism and Creativity

	Openness to Experience	Agreeableness	Classical Arts	Modern Arts	Artistic Activities
	(1)	(2)	(3)	(4)	(5)
Individualism	0.046*	-0.038**	0.066***	0.060***	0.052***
	(0.028)	(0.015)	(0.021)	(0.019)	(0.016)
Covariates	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Survey Year	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes
Outcome mean	4.69	5.50			
R-squared	0.04	0.03	0.05	0.10	0.04
Origins	63	63	63	63	63
Observations	5,970	5,970	6,789	6,789	6,789

Notes: The table shows the results for the outcomes indicated in the column header in the sample of first-generation migrants for the German socio-economic panel (2017-2019 waves; pooled OLS estimations). Results in Columns (1)-(2) show results for the openness to experience and agreeableness Big Five scores obtained by averaging the respective three item scores. The cultural outcomes in Columns (3)-(5) measure the self-reported frequency of the respective cultural-creative activity on a five-point Likert scale. They are standardized to a mean of 0 and a standard deviation of 1 in the full sample. Individualism refers to Hofstede's index and is standardized to a mean of 0 and a standard deviation of 1 in the full sample. *Covariates*: age, age squared, and a gender dummy. *Fixed effects:* survey wave and continent of origin. Standard errors clustered at the origin-country level reported in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: SOEP, Hofstede (2001).

Since individualist culture is strongly related to outcomes of the creative process at the aggregate and individual level, the question emerges whether individualism affects more general, non-economic forms of creative expression or interest. While openness to experience is an important creativity trait, it is not an all-encompassing creativity measure. For instance, Waldman, Atwater, and Davidson (2004) show that individualism explains performance in a group discussion independent of the explanatory power of the Big Five. This highlights that while individualism may be related to the Big Five components, it remains a separate dimension of personality. The SOEP data lend themselves to further creativity analyses since detailed information on respondents' leisure activities is available. Engaging in artistic and cultural activities may capture aspects of creativity not reflected in personality traits but rather in actions.

Columns (3) to (5) show the relationship between individualist culture and cultural interest. For all three domains of cultural interest—attending classical and contemporary cultural events (such as concerts) and being culturally active (for instance, by playing an instrument)—the individualism coefficient is positive and highly significant. An increase in individualism by one standard deviation is associated with an increase in attendance of cultural events of 6.6 percent of a standard deviation for classical arts and a very similar 6.0 percent of a standard deviation for modern arts. Engaging in own artistic endeavors—such as playing an instrument or drawing—increases by 5.2 percent of a standard deviation if individualism increases by one standard deviation.

To benchmark these coefficient sizes, for classical arts consumption, the individualism coefficient is almost identical to the gender difference (with women consuming significantly more classical arts). For artistic activities, the individualism coefficient amounts to half of the gender difference. Thus, the individualist focus on self-fulfillment and self-expression as well as, perhaps, the appreciation of unique experiences and others' creative achievements is also reflected by private life choice regarding the consumption and creation of arts and culture. Overall, the evidence from the SOEP suggests that—at least in the cultural context of Germany—more individualist migrants are slightly but significantly more likely to be creative and creativity-appreciating types both in personality and behavior. From a purely economic perspective, the results pale in comparison to the magnitude and economic significance of the results for occupational selection, knowledge diffusio on the job, and patenting, which remain the focus of this paper.

VI. Individualism and Innovation Output

Sections V.A and V.B show that individualism affects different innovation-conducive career choices and on-the-job behaviors, which to an extent can be thought of as *inputs* of an individual innovation production function. This section is dedicated to studying if and how individualism affects innovation *output*—in general and specifically through these behaviors. In this context, innovation output is measured in two ways: Through general productivity as captured by wages, and through patents as a specific, countable measure.

Turning to individual wages to micro-found aggregate growth effects is very much in line with Phelps' (2013) concept of *mass flourishing* as a driver of modern growth: Even subtle or informal grassroots innovations as well as process innovations should manifest themselves as productivity advantages. Thus, as the most inclusive productivity measure, wages are able to capture the effect of individualism on the broad innovative potential of a society. After Section VI.A establishes the individualism wage premium, the mediation analysis in Section VI.B disentangles the substantial relative contributions of the different individualism-induced innovation behaviors to this wage premium.

Since individual patent data cannot be linked to PIAAC, a similar mediation analysis for this more direct innovation output measure is not feasible. However, Section VI.C provides detailed evidence on the relationship between individualism and patenting behavior in general. Taken together, the analyses demonstrate that the positive effect of individualism on innovation behaviors carry over to innovation output.

Table 4. Individualism and Hourly Wages

	Migrants		Natives
	(1)	(2)	(3)
Hofstede IDV	0.079***		
	(0.024)		
Person-level IDV		0.121***	0.111***
		(0.026)	(0.002)
Covariates	Yes	Yes	Yes
Fixed Effects			
Destination Country	Yes	Yes	Yes
Origin Continent	Yes		
Migration Year		Yes	
Year x Destination		Yes	
Origin Country		Yes	
Origin x Destination x Year		Yes	
Outcome mean	3.21	3.19	3.87
R-squared	0.89	0.96	0.94
Origins	66	170	
Observations	3,744	5,177	73,405

Notes: The table summarizes the relationship between individualism and log hourly wages (excluding bonus payments for wage and salary workers). For details on wage information in PIAAC, see Section III.A. The specifications follow Table 5 and Table 7. Standard errors reported in parentheses are heteroskedasticity robust for natives and clustered at the origin-country level for migrants.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PIAAC, Hofstede (2001).

A. *Individualism and Wages*

As innovation is a fundamental cause of economic growth (Romer 1990; Sampson 2023), a higher degree of innovativeness should pay off in the labor market in the form of a productivity and wage premium. To test this hypothesis, the underlying total relationship between individualism and wages must be established first. Table 4 summarizes the results of estimating the individualism wage premium in the sample of migrants and natives—as

measured by log hourly wages. In all specifications, individualism comes with a significantly positive and economically meaningful wage premium. In the main specification shown in Column (1) that underlies the mediation analysis, hourly wages increase by 7.9 percent for a one-standard-deviation increase in individualism.[16] When individualism is measured at the *person level*—based on the measure developed in Section III.C—instead of the origin-country level in specification (2), which relies only on *within-origin-country* variation in individualism, the wage premium is larger. It also persists in the sample of natives which abstracts from any migration context and is also based on the person-level individualism measure. Following the standard economic assumption that wages capture individual productivity, this is an economically highly relevant productivity effect.

B. *Opening the Productivity Black Box*

The statistically and economically significant individualism wage premium calls for a mediation analysis to uncover the mechanisms behind this result. Specifically, the mediation analysis answers two questions: What are the tangible economic consequences of the innovation behaviors at the individual level? And, what is the relative importance of each innovation-conducive behavior in explaining the individualism effect on wages?

In recent years, the method popularized by Heckman, Pinto, and Savelyev (2013) and Heckman and Pinto (2015) has become an important tool for economic mediation analyses with multiple mediators. By estimating the outcome as a linear combination of the mediators, this approach ultimately provides insights into the relative contributions of all specified mechanisms to the overall effect. Thus, it allows for a ranking of the relative importance of different channels through which individualism affects productivity. The analysis relies on the assumption that a causal effect of the variable of interest and the mediators on the outcome variable can be estimated as well as a causal effect of the variable of interest on the other mediators (all conditional on control variables and fixed effects). All relevant mediators need to be included in the analysis—immediately implying that they can and should be included at the same time and not (only) in a one-by-one approach. Appendix C discusses the mediation approach and assumptions formally.

Table 5 shows the regressions that underly the mediation analysis, and Figure 2 visualizes the relative contributions of the four distinct mediators. Columns (2) to (6) reveal that the mediators are positively related to the outcome separately and when included simultaneously. When all mediators are included, the individualism coefficient itself is still positive at a 1.2 percent wage premium but turns statistically insignificant. The full mediation regression already highlights the power of the specified mechanisms in explaining the individualism effect on wages. Indeed, the joint contribution of all innovation

[16] This wage return is very comparable in size to the 8.4 percent premium reported in Hartinger et al. (2021) for the PIAAC round 1 & 2 sample.

mediators amounts to 44 percent of the total 7.9 percent wage premium of individualism—constituting the main result of the mediation analysis.

Together with numeracy skills as a measure of the human capital channel, 84 percent of the individualism wage premium can be explained. Since the innovation-conducive on the job behaviors measure knowledge diffusion through learning behaviors and since innovation and human capital are also conceptually related (Lazear 2004), this study does not attempt to disentangle a human capital versus an innovation channel. Instead, I focus on innovation behaviors that are naturally related to individual human capital.

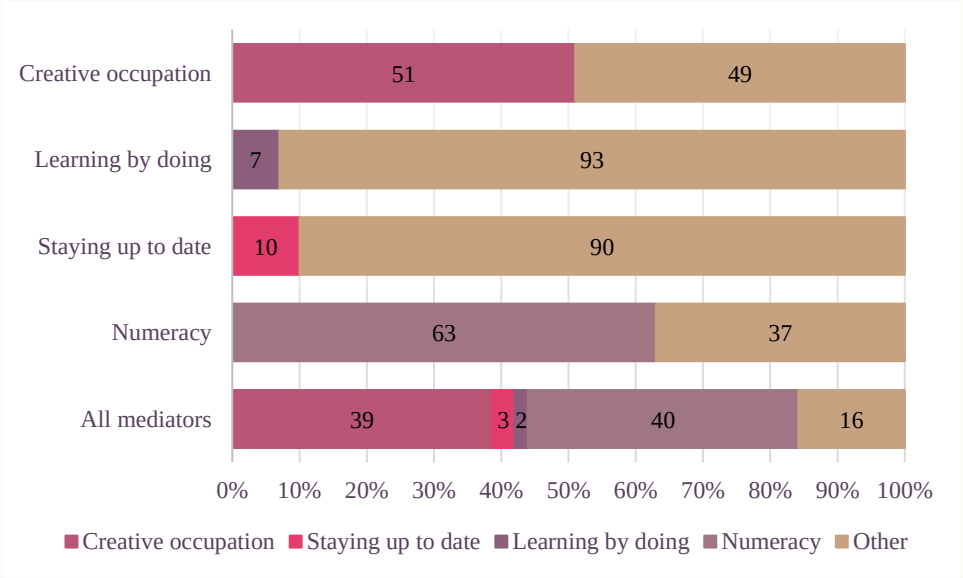

Figure 2. Mediation Analysis

Notes: The figure summarizes the main results of the mediation analysis for each mediator separately and for all mediators jointly. The mediation analysis is based on Table 5 as well as Table 1 and Table 2.
Data sources: Hofstede (2001), PIAAC.

By a wide margin, selection into creative occupations (39 percent explained) and cognitive skills (40 percent explained) are the mediators with the highest explanatory power. While keeping up to date and learning by doing are significant mechanisms, their contributions of 3 and 2 percent explained are small compared to the two most important mediators. These findings highlight the importance of career choice as the innovation-related mechanism through which individualism affects individual productivity. Only 16 percent of the individualism wage premium remain unexplained by the innovation- and human-capital-related mediators. These 16 percent could include non-cognitive wage-relevant skills and preferences associated with individualism—such as negotiation skills and a preference for an excellent job match.

Overall, the mediation analysis reveals the strong and economically significant role of innovation-focused behaviors in explaining the positive individualism effect on productivity. In doing so, it underlines the importance of investigating innovation behaviors

comprehensively and cements the micro foundation of the aggregate innovation effects by highlighting key mechanisms.

Table 5. Mediation Analysis: Individualism, Innovativeness, and Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.079***	0.038**	0.070***	0.073***	0.029	0.012
	(0.024)	(0.015)	(0.022)	(0.023)	(0.019)	(0.013)
Creative occupation		0.531***				0.401***
		(0.047)				(0.027)
Staying up to date			0.085***			0.028***
			(0.007)			(0.007)
Learning by doing				0.073***		0.020***
				(0.013)		(0.007)
Numeracy					0.209***	0.133***
					(0.025)	(0.017)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	3.21	3.21	3.21	3.21	3.21	3.21
R-squared	0.89	0.91	0.89	0.89	0.91	0.92
Origins	66	66	66	66	66	66
Observations	3,744	3,744	3,744	3,744	3,744	3,744

Notes: The table shows the results of the regressions that together with Table 1 and Table 2 underly the mediation analysis that culminates in Figure 2. The outcome is log hourly wage. See text as well as Table 1 and Table 2 for a description of all innovation-related mediator variables. Numeracy refers to the first plausible value of the PIAAC numeracy score and has been standardized to a mean of 0 and a standard deviation of 1 in the full international sample. Observations are weighted, giving each destination country the same weight. *Covariates*: age, age squared and a gender dummy. *Fixed effects:* destination country and continent of origin. Standard errors clustered at the origin-country level reported in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PIAAC, Hofstede (2001).

C. *Patenting*

Moving on from wages as a general measure of innovative productivity to patenting as a direct innovation output measure, Table 6 presents the results from estimating equation (2) based on the aggregate epidemiological approach. Recall that the Miguélez and Fink (2013) database offers yearly count data for patents filed within the international PCT system by migrant origin and destination country. Within each destination country, patenting behavior is compared between migrants from different origin countries. Variation in individualism is, thus, based on the 68 origin countries of the migrants for which a Hofstede individualism value is available. Before more sophisticated count-data-specific estimators are used, even simple OLS specifications help clarify the overall direction and strength of the effect. Conditioning on destination country (which is the essential prerequisite to make the epidemiological approach meaningful), patent filing year (to account for the longitudinal structure of the data set), their full interaction, and continental fixed effects (which refer to the country of origin of the migrants), a positive and significant relationship between

individualism and patenting behavior emerges. This main finding is in line with the cross-country results in Gorodnichenko and Roland (2017). In a first step, Column (1) presents OLS estimation results for a binary measure indicating whether there was any patenting activity for an origin-destination pair in a year. This simple linear probability model reveals that the probability of observing patenting activities at the extensive margin increases significantly with individualism. Focusing on the intensive margin, Column (2) focuses only on non-zero observations and confirms the positive relationship. Even within the subsample of origin countries whose migrants do patent in a given destination country in a given year, migrants from more individualist origins generate more patents. If individualism increases by a standard deviation—comparable to the difference between Germany (with a score of 67 on the Hofstede scale) and the United States (91), the patent count in this non-zero subsample increases by 22 patents, which corresponds to a 90 percent increase relative to the average patent count of 24. While this OLS specification captures only the intensive margin of patenting conditional on non-zero patenting activity, the specification in Column (3) confirms the finding in the full sample. Again, the individualism coefficient is large and highly significant, indicating a positive effect of individualism on innovation.

Table 6. Individualism and Patenting

	Binary Patent Measure	Non-Zero Observations	Count Data (Full Sample)			OECD Migration	Single Inventors
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	Neg. Bin.	Poisson	Poisson	Poisson
Individualism	0.142***	22.042***	7.419***	1.144***	1.084***	1.005***	0.941***
	(0.018)	(6.089)	(1.964)	(0.100)	(0.292)	(0.283)	(0.163)
Ln(alpha)				0.992***			
				(0.102)			
Fixed Effects							
Destination	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Destination	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.35	24.05	8.26	8.25	8.26	12.12	0.88
(Pseudo) R-squared	0.34	0.13	0.13	0.19	0.67	0.69	0.38
Origins	68	68	68	68	68	32	67
Observations	53,502	18,336	53,502	53,559	53,502	21,592	17,716

Notes: The table shows the results for the number of patents in the PCT system filed by migrants per origin-destination pair per year. The results are based on the sample of non-zero observations (Column (2)), the full sample (Columns (1) and (3)-(5); slight discrepancies in sample size are due to technical reasons), the sample of migrants originating from OECD countries and residing in OECD countries (Column (6)), and the sample of patents filed by single inventors (Column (7)). Columns (1)-(3) use OLS, while Columns (4)-(7) summarize negative binomial and Poisson results. Individualism refers to Hofstede's individualism index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Fixed Effects: Destination* refers to the inventors' country of residence. *Year* refers to the patent's priority year, which is the year the patent is first filed anywhere. *Origin continent* refers to the continent of the inventors' origin country. *Origins* refer to the number of origin countries. Standard errors clustered at the origin-country level reported in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: PCT, Miguélez and Fink (2013), Hofstede (2001).

To tackle the extensive margin from a methodological perspective that is more appropriate for count data, Columns (4) and (5) show the results for negative binomial and Poisson regressions that confirm the strong positive results from the previous specifications. Like most patent data sets, the Miguélez and Fink (2013) data contain zero values (with no migrants from the Philippines living in Italy patenting in the PCT system in 2010, for instance). Simple OLS fails to properly account for this particularity in the data structure. It is reassuring that the negative binomial results and Poisson results are very similar to each other, with Poisson serving as the main specification for the subsequent analyses.[17] If individualism increases by one standard-deviation, the expected log count of patents

[17] The negative binomial estimator is not designed for high-degree fixed effects due to the incidental parameter problem Jeffrey M. Wooldridge (1999). The Poisson estimator is the most robust estimator in the context of high-degree fixed effects Nicholas L. Brown and Jeffrey M. Wooldridge (2021), but inferior to the negative binomial in the case of overdispersion (a data feature highlighted by the significant alpha parameter). Zero-inflated models as another common count data estimation approach would only be a suitable option in this setting if the data generating process generating excess zeroes differed from the general data generating process underlying the number of patents. This would be the case if, say, laws prevented migrants from 25 countries from filing patents in their destination country. To the best of my knowledge, the PCT regulations do not plausibly justify the use of zero-inflated models.

increases by 1.084 in—corresponding to a multiplicative factor of 2.96—in Column (5) when origin continent, destination country, and year are kept constant.

Two specific subsamples of inventors are of additional interest in this context. The sample of OECD-OECD migrants zooms in on high-skilled migration and confirms the findings for the main sample. Additionally, the individualism coefficient is comparable in size in the sample of single inventors, i.e., individuals who patent by themselves without the help and collaboration of co-inventors at a larger corporation or research institute. As the main channels through which individualism affects innovation are suspected to be individual career drive and motivation as well as a focus on outstanding creativity rather than extensive collaboration, this result is in line with theoretical predictions. Overall, Table 6 shows a strong and positive relationship between individualism and aggregate patenting behavior among migrants in a large set of destination as well as origin countries.

Table D6 summarizes robustness checks that introduce controls for tertiary education, total factor productivity, GDP levels, and other aspects of culture at the level of the origin country. Once all controls are added simultaneously, the individualism effect is significant at the 10 percent level in this richest specification in this demanding model that deactivates several origin-country mechanisms. The individualism coefficient is noticeably larger than that of the other cultural dimensions commonly associated with innovation output, cultural risk (Levine and Rubinstein 2017; Kritikos 2022). and time preferences (Sunde et al. 2022). While Table D6 already covers many potential confounders, the individualism results for patenting also remain robust when migration costs are controlled for in Table D5. Since the aggregate epidemiological approach in combination with longitudinal data and a count-based outcome has not been well established in the literature yet, I present several specification checks: In Table E6, the main results are replicated without sample restrictions and for the subsamples of Hofstede and top-patenting destinations as well as for the subsample that excludes the top-patenting origin-countries. Finally, only the best-quality PCT years of 2004-2011 are considered. All checks show that the individualism effect does not appear to be driven by particularities of the PCT data or a specific group of origin or destination countries. Table E7 looks at the cross-section results for 2011, which eliminates the longitudinal structure of the data and is more suitable for logit and negative binomial regressions. Table E8 addresses potential concerns regarding a measurement by using the five-year moving average patent count as the outcome and controlling for the size of the inventor diaspora of the respective origin country, despite the latter possibly creating a bad control problem. This analysis rules out a mechanical relationship between individualism and patenting that is simply driven by a larger pool of migrants from individualist countries overall. The table also provides several alternative ways of clustering standard errors. Finally, Table E9 shows results based on alternative individualism-collectivism measures. In all validity checks, the strong relationship between individualism and patenting proves robust to adjustments to the sample of interest, measurement, and the estimation of standard errors.

VII. Robustness

A. *Person-Level Individualism Approach*

To solidify the relationship between individualism and innovation behaviors, this section describes the results for occupational selection and behavior on the job based on the personal individualism approach. This approach broadens the perspective of the previous results in two ways: First, it allows for a shift from migrants to natives to validate the results in a setting that is not affected by selection into migration, migration waves, different motives behind migration, or any other specificities of the migration context. Second, it also allows for the introduction of origin-country fixed effects in the epidemiological approach, thereby holding constant all origin-country characteristics.

Table 7 presents a the main results for the enhanced private-life index for natives and first-generation migrants, while Table E3 shows the corresponding results for the broad index developed in Hartinger et al. (2021) and Table E4 and Table E5 show the full set of results for all outcomes. In the large sample of natives, all individualism coefficients are highly precisely estimated and positive. Confirming the results from the epidemiological approach, individualism increases the probability of working in a creative-innovative or research-focused occupation. For a one-standard-deviation increase in personal individualism, the probability of selecting into a creative occupation increases by 11.6 percentage points, which corresponds to a third of the 0.36 share in the sample. This coefficient is slightly larger than in the epidemiological approach but remains in the same range. The relationship between individualism and self-employment is once again significant but weak in size with a coefficient size of 0.8 percentage points—compared, for instance to the 5.7 percentage point gender difference in self-employment.

Additionally, this result is not precisely estimated in the first-generation specification. Here, the sample size increase due to the wider availability of the personal measure now allows for the inclusion of year-of-migration fixed effects in addition to the valuable origin-country fixed effects (fully interacted with year of migration and destination country). This specification mitigates concerns regarding omitted origin-country factors and produces coefficients that are very similar in size to those in the specifications based on natives. Thus, the results in Table 7 confirm the findings presented in Table 1 and Table 2 for the population of natives and for variation based on a person-level individualism measure. Despite the remaining concerns of reverse causality that this approach undoubtedly brings with itself, it provides a new layer of evidence for a strong relationship between individualism and various dimensions of innovation and enhances the results obtained via traditional country-level individualism measures.

Table 7. Individualism and Innovativeness: Person-Level Evidence

	Natives			First-Generation Migrants		
	Creative Occupation	Self Employed	Keeping up to date	Creative Occupation	Self-Employed	Keeping up to date
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.115***	0.008***	0.206***	0.115***	0.012	0.202***
	(0.002)	(0.001)	(0.003)	(0.014)	(0.009)	(0.031)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Migration Year				Yes	Yes	Yes
Year x Destination				Yes	Yes	Yes
Origin Country				Yes	Yes	Yes
Origin x Destination x Year				Yes	Yes	Yes
Outcome mean	0.36	0.18		0.39	0.12	
R-squared	0.11	0.10	0.10	0.69	0.66	0.63
Origins				170	170	170
Observations	99,144	99,144	99,144	6,328	6,328	6,328

Notes: The table shows the results for the outcomes indicated in the column header in the sample of natives in Columns (1)-(3) and in the sample of first-generation migrants in Columns (4)-(6). Observations are weighted, giving each destination country the same weight. Individualism refers to the private-life-based personal individualism index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Covariates*: age, age squared, and a gender dummy. *Fixed effects:* country for natives; the full set of interactions between destination country, migration year, and origin country for migrants. Standard errors reported in parentheses are heteroskedasticity-robust for natives and clustered at the origin-country level for migrants. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PIAAC.

B. *Regional Approach*

To provide further evidence on the relationship between individualism and innovation, this section presents the results for the region-level approach, which gently bridges the gap between the individual-level results in this paper and the country-level results established in the literature. In previous region-level work, Boschma and Fritsch (2009) relate the size of the creative sector to cultural values like openness and labor-market conditions, and Mostaghel, Oghazi, and Patel (2023) look at individualism and county-level entrepreneurship in the US. The regional approach used here does not rely on the migration context like the epidemiological approach and further circumvents omitted variable concerns at the individual-level. Table 8 summarizes the results stemming from regressing the key occupational selection outcomes and the number of regional patents on regional individualism and country fixed effects. Thus, only regions *within the same country* are compared to each other since they differ with respect to regional individualism. To measure individualism, I use the aggregate of the person-level individualism index presented in earlier sections of this paper at the region level.

Table 8. Individualism and Innovativeness: Region-Level Evidence

	Patents	Creative Occupations	Bohemian	Research Occupations	Self-Employment	Keeping up to date
	(1)	(2)	(3)	(5)	(6)	(1)
Individualism	111.207***	0.092	0.042***	0.056**	-0.019	0.392***
	(28.704)	(0.072)	(0.012)	(0.023)	(0.024)	(0.143)
Fixed Effects						
Country	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	75.72	0.32	0.02	0.06	0.21	
R-squared	0.55	0.68	0.33	0.61	0.87	0.71
Observations	196	270	270	270	270	270

Notes: The table shows the results for the outcomes indicated in the column header for large (TL2) OECD regions. Individualism refers to the regional aggregate of the enhanced person-level individualism used in Table 7. Patents refer to the count of patents filed per region per 100,000 inhabitants in 2015 as per the OECD regional database. *Fixed effects:* Country in which the region is located. Heteroskedasticity-robust standard errors reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PIAAC, OECD.

For all main outcomes except the share of self-employed in the region, the direction of the individual-level findings is confirmed: More individualist regions patent more, have a larger creative as well as research sector. In particular, if individualism increases by one standard deviation, the number of patents per 100,000 inhabitants filed in a region in 2015 increases by 113 patents. This increase amounts to 150 percent of the 75-patent average. All results except for self-employment and the share of creative occupations are statistically significant. While the former's lack of significance should likely be attributed to the general lack of robustness for this outcome, the latter's may be explained by the breadth of this concept that bundles a wide range of diverse occupations—making it prone to a lot of compositional noise between regions. The more refined and specialized categorizations of innovative occupations have a more reliable predictive power in the regional context. The positive relationship between individualism and knowledge diffusion on the job among migrants is also visible at the region level. Knowledge diffusion through keeping up to date on the job is significantly more prominent in more individualist regions within the same country.

While the region-level results add an interesting perspective and circumvent some of endogeneity concerns of the individual-level approaches, they are not to be interpreted in isolation due to the lack of exogenous variation. Instead, they provide a complementary perspective on the stable patterns in the data. It is reassuring to see that the relationship between individualism and innovation-conducive job selection and approach to the job at the individual level carries over to the regional level. Additionally, results for patenting as a key innovation outcome are also reflected at the regional level. Thus, the regional results are able to tie together the findings on innovation-conducive behaviors and innovation output in a way that complements the mediation analysis in the previous section.

VIII. Conclusion

From Steve Jobs to Karl Lagerfeld, Lady Gaga, and Gyro Gearloose—some of the best-known innovators seem to be paragons of individualism in their unique achievements, their breakthrough creations, and, occasionally, their eccentricity. Their biographies make it easy to believe that there is a systematic relationship between individualism and innovation; at least among star innovators, that is. This paper investigates the effect of individualism on individual innovation—from occupational selection and behavior on the job to creative expression and patenting behavior—from a comprehensive perspective. Are individualist success stories limited to the top one percent or is individualism the cultural driving force behind a broad innovative potential in a society? The individual-level results for a variety of dimensions of innovation and creativity are a reflection of the broader pattern established at the macroeconomic level. Using international data in combination with the epidemiological approach, I show that individualism is systematically and positively related to selection into innovative and creative professions. While these are particularly tangible and well-structured facets of innovation, I find similar results for individual job interpretation between and within occupations: More individualist people spend more of their time at work learning and staying up to date with the technological progress in their field—clearly innovation-conducive behaviors related to the diffusion and adoption of know-how. Finally, even though individualism is only weakly related to creativity traits, there is a meaningful relationship between individualism and cultural-creative expression. Assessing the extent to which the individualism-induced individual innovativeness manifests in a tangible economic way, this paper is the first to show that the job-related innovation behaviors explain a large share of the positive effect of individualism on wages. A positive effect on patenting behavior solidifies the relationship between individualism and innovation output.

Naturally, this study comes with a set of limitations due to the non-experimental nature of the variation in individualism: Several approaches that rely on complementary sources of variation in individualism (with estimations at the person and region level) mitigate the concerns regarding omitted origin-country factors—such as unobserved institutions. Their causal interpretation is in turn limited by potential reverse causality through simultaneous measurement of individualism and the outcomes. Nonetheless, the results presented in this paper rely on and even go beyond the well-established epidemiological approach. The revealed patterns in the micro-level evidence tell a consistent story of the role of individualism in innovation even when major confounders are accounted for and complementary sources of variation in individualism are used.

The breadth of the impact of individualism on individual innovation choices supports the hypothesis that this dimension of culture acts as a non-cognitive skill and motivator that allows individuals to strive for innovation and unlock their creative potential not just in top-level ambitious entrepreneurship but across a wider range of careers and occupations as well as in their private life. These different aspects of innovation represent different mechanisms

through which individualism affects economic growth—with different policy implications. Some of these outcomes, such as selection into creative and artistic occupations, are related to growth through agglomeration effects (Florida 2002). A rich cultural sector attracts other bohemians and innovators by acting as a non-monetary commodity. Other outcomes, such as creativity and research, are expected to have a direct impact on growth through structural innovation. Finally, learning behaviors may affect growth through the diffusion of knowledge and an accumulation of intangible and intellectual capital of a firm or society, which has gained research interest over the past years (Piekkola 2020; Biasi, Deming, and Moser 2021). Thus, with its multifaceted view of innovation, this paper contributes to our understanding of the individual-level forces that, in the aggregate, shape the macroeconomic growth and innovation effects of individualism through several distinct mechanisms.

However, this paper does not rank or judge cultures. Rather, an understanding of how culture enters the individual and collective innovation production function is an important puzzle piece in fostering intercultural communication and collaboration. In times of much discussion and concern regarding the speed of innovation (Park, Leahey, and Funk 2023), looking at such atypical drivers of innovation may provide intriguing ways forward.

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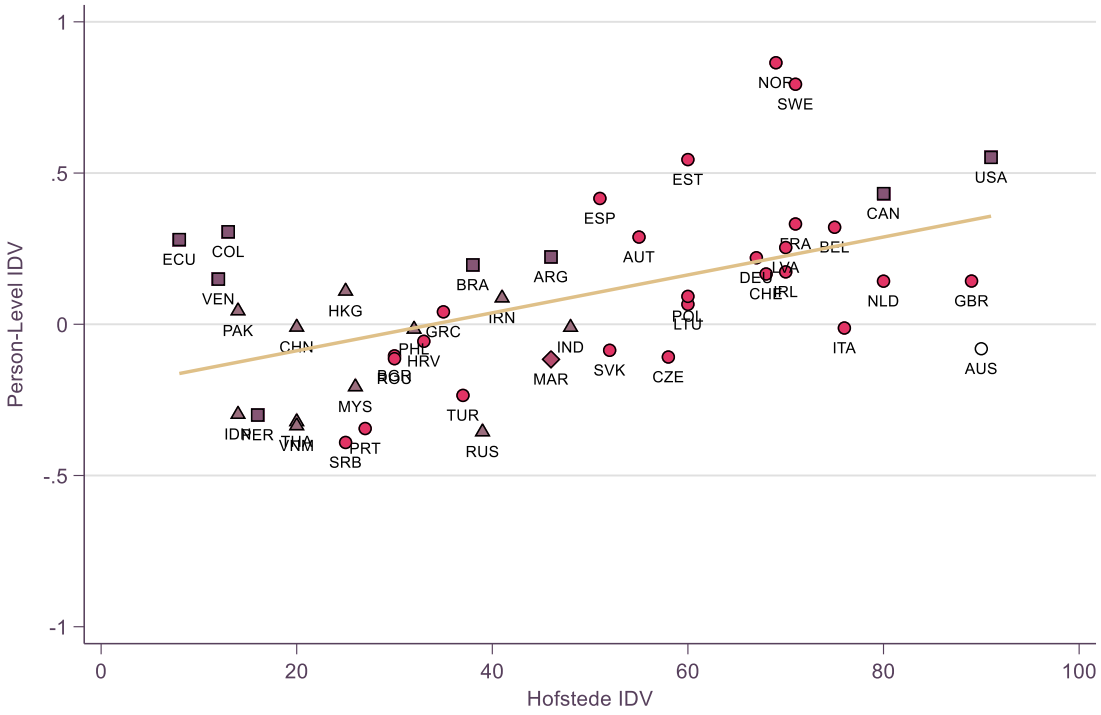
APPENDIX

A. Descriptive Statistics

Figure A1. Person-Level Individualism Index and Hofstede Individualism



Notes: The figure illustrates the correlation between the Hofstede individualism index and the origin-country-level average of the person-level individualism index for first-generation migrants. Only origin countries with more than 30 migrant observations are included.
Data sources: Hofstede (2001), PIAAC.

Table A1—Descriptive Statistics

	(1)	(2)	(3)
Panel A. PIAAC Epidemiological			
	First-generation migrants		
	Mean	SD	N
Culture			
Hofstede IDV	44.8	21.9	4,627
Hofstede LTO	52.5	21.6	4,627
Hofstede UAI	64.7	24.9	4,627
Career and skills			
Creative occupation	0.427	0.495	4,627
Bohemian	0.030	0.170	4,627
Artist	0.007	0.082	4,627
Research occupation	0.105	0.307	4,627
Self-employed	0.135	0.342	4,627
Keeping up to date	2.95	1.40	4,617
Learning by doing	3.50	1.40	4,610
Learning from coworkers	3.13	1.39	4,224
Log hourly wage (PPP USD)	3.20	1.53	3,758
Numeracy	256.0	62.4	4,627
Demographics			
Age	40.9	11.3	4,627
Female	0.514	0.500	4,627
Year of migration	1992	14.1	4,627

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B. PIAAC Person-Level						
	First-generation migrants			Natives		
	Mean	SD	N	Mean	SD	N
Culture						
Person-level IDV	0.067	0.961	6,328	0.030	0.979	99,145
Career and skills						
Creative occupation	0.390	0.488	6,328	0.355	0.479	99,145
Bohemian	0.027	0.161	6,328	0.021	0.143	99,145
Artist	0.006	0.076	6,328	0.003	0.057	99,145
Research occupation	0.097	0.296	6,328	0.067	0.249	99,145
Self-employed	0.125	0.330	6,328	0.177	0.382	99,145
Keeping up to date	2.94	1.42	6,328	3.09	1.38	99,145
Learning by doing	3.48	1.41	6,314	3.51	1.37	99,001
Learning from coworkers	3.13	1.41	5,817	3.17	1.35	87,085
Log hourly wage (PPP USD)	3.19	1.51	5,177	3.87	2.14	73,406
Numeracy	251.9	61.1	6,328	263.5	56.6	99,145
Demographics						
Age	40.8	11.4	6,328	40.3	12.4	99,145
Female	0.506	0.500	6,328	0.481	0.500	99,145
Year of migration	1992	13.7	6,328			

	(1)	(2)	(3)
Panel C. SOEP Data			
	First-generation migrants		
	Mean	SD	N
Culture			
Hofstede IDV	45.0	17.6	6,789
Creativity			
Openness (average)	4.69	1.26	5,970
Agreeableness (average)	5.51	1.00	6,067
Classical arts	1.58	0.70	6,789
Modern arts	1.79	0.80	6,789
Artistic activities	1.76	1.12	6,789
Demographics			
Age	45.3	14.8	6,789
Female	0.530	0.499	6,789

	(1)	(2)	(3)
Panel D. PCT Data			
	First-generation migrants		
	Mean	SD	N
Culture			
Hofstede IDV	50.4	24.6	53,502
Hofstede LTO	49.4	21.4	53,502
Hofstede UAI	66.0	23.3	53,502
Patents			
Number of patents	8.259	100.478	53,502
Year	1998	8.9	53,502

Notes: The table presents summary statistics for key variables. Panel A refers to the PCT patent data from Miguélez and Fink (2013). Panel B refers to the PIAAC estimation sample of first-generation migrants in the epidemiological approach. Panel C refers to the PIAAC estimation samples of native and first-generation migrants in the person-level individualism approach. Panel D refers to the estimation sample of first-generation migrants in the epidemiological approach for the 2017-2019 waves of the German Socioeconomic Panel.

B. Description of Further Data Sources and Control Variables

B.1 German Socioeconomic Panel

The German Socio-Economic Panel (SOEP) is one of the most widely used German data sets. It is a yearly representative household panel survey covering the resident population of Germany starting in 1984 (Wagner, Burkhauser, and Behringer 1993). The SOEP covers a wide range of questions measuring respondents' preferences and attitudes as well as their professional and leisure activities. Many items are not included in every wave of the SOEP, however. To investigate the relationship between individualism and creativity in the SOEP based on the epidemiological approach, I use data from the recent 2017-2019 waves. In its pooled OLS setting, the analysis covers up to 6,800 first-generation migrants from 63 different origin countries for which a Hofstede individualism score is available.

The analysis focuses on the Big Five personality traits that are available in the 2017 and 2019 waves and active and passive cultural engagement (2017-2019). To measure the Big Five personality traits (openness to experience, conscientiousness, extraversion, agreeableness, neuroticism), the SOEP uses a short scale where each dimension of personality is measured via three descriptive statements that respondents rate on a seven-point Likert scale ("applies fully" to "does not apply at all"). I focus on openness to experience, commonly regarded as the creativity trait among the Big Five, which is related to entrepreneurship and innovativeness (Costa and McCrae 1992; Zhao and Seibert 2006; Kritikos 2022). The SOEP openness items are as follows: "I am original", "I value artistic experiences", and "I have lively imagination". The other dimension of interest is agreeableness, which has been found to affect entrepreneurial longevity (Caliendo, Fossen, and Kritikos 2014). The three items for each Big Five trait are averaged to obtain the final score. Active and passive cultural engagement is captured by three separate items on respondents' leisure activities: They measure how often a respondent visits "the opera, classical concerts, the theater, and exhibitions", "the cinema, pop and jazz concerts, and nightclubs", and actively engages in "artistic and musical activities". Each item is scored on a five-point scale with the options "daily", "weekly", "monthly", "rarely", and "never". The scales are recoded so that higher values indicate more frequent behaviors and standardized to a mean of 0 and a standard deviation of 1 in the full sample.

B.2 Control Variables

A series of origin-country and origin-destination-pair control variables are used throughout this study to validate the results of both the patent and PIAAC analyses.[18] They stem from a variety of sources. Missing values in the control variables are imputed by the mean with details available in the respective table notes.

The cultural controls are based on the Hofstede (2001) database. Specifically, uncertainty avoidance and long-term orientation are included. They capture cultural risk and time

[18] Since the results based on the SOEP are comparatively weak statistically and, more importantly, economically in the main specification, robustness checks for these analyses are not included.

preferences. Like individualism, they are measured on a scale from 0 to 100 in the index. Uncertainty avoidance is one of the original Hofstede dimensions from the 1970s, while long-term orientation was added to the framework later (Hofstede 2001; Hofstede and Minkov 2013). There are alternative measures for cultural time and risk preferences, for instance, through the Global Preferences Survey (Falk et al. 2018). Using these alternative measures does not affect the main results, which is why they are omitted for expositional reasons.

Aside from culture, an important set of variables measures economic conditions in the origin country that are potentially related to individualism and innovation. The 2015 Global Creativity Index data underlying Figure 1 are provided by the Martin Prosperity Institute. To account for educational quality, the share of the population that has completed tertiary education based on the measure from Barro and Lee (1996) is used as the extent of *higher* education is expected to be particularly relevant in the context of innovation. The measure contains variation over time (in five-year intervals), which is used in the patent (patent priority year) and career analyses (year of migration) to approximate pre-migration institutions as accurately as possible. The same procedure is used for the educational selection measure taken from Brücker, Capuano, and Marfouk (2013).

Log yearly gross domestic product (expenditure-side real GDP at chained PPPs in million 2011 US dollars) and yearly total factor productivity (TFP at constant national prices; only used in the more aggregate patent analysis) are taken from the Penn World Table 9.0, which is available for 182 countries (Feenstra, Inklaar, and Timmer 2015). To account for migration costs, three country-pair controls from the CEPII database are used (Mayer and Zignago 2011).[19] They capture contiguity, geographic distance, and (ASJP-based) linguistic proximity as captured by similarity in pronunciation of a set of words. Genetic distance between origin and destination country is taken from Krieger, Renner, and Ruhose (2018). Finally, the distance in economic inequality is measured through the decade-specific distance in the Gini coefficients from Hartinger et al. (2021). In the non-patent specifications, the number of patent applications per 10,000 origin-country residents through the PCT or nationally is used as an additional control variable at the origin-country-year-of-migration level based on World Bank data. This control variable immediately illustrates the bad control concerns associated with most control variables. Thus, they are not included in the main specification and relegated to robustness checks.

[19] Source: http://www.cepii.fr/cepii/en/bdd_modele/bdd.asp

C. Mediation Approach and Assumptions

The mediation analysis in this study differs from the standard case in two ways: First, while in many mediation analyses the focus of the underlying research study is on the main effect of the variable of interest on the final outcome, this paper has mainly been concerned with establishing the effect of individualism on the *mediators*. Thus, the missing links in this analysis are the effect of individualism on productivity as the final outcome (see Section VI.A) as well as the effects of the mediators themselves on productivity. Second, despite career choice constituting the first and most important innovation-related mediator, not all occupational choice variables presented in Table 1 can be included in the mediation analysis simultaneously: Creative occupations, Bohemians, artists, and research occupations are all binary occupational categories based on ISCO-08 codes. They are not mutually exclusive, with, for instance, Bohemian occupations constituting a subset of all creative occupations. Thus, to allow for a meaningful interpretation of the mediation results, only the broadest classification—creative occupations following Florida (2002)—is used in the analysis. Since the effect of individualism on self-employment is unstable at best, self-employment is not considered in the mediation analysis.

Included, of course, are the innovation-conducive behaviors on the job from Table 2. However, learning from co-workers turns out to be a mediator with a negative coefficient in the long mediation estimation. I follow the implementation of the mediation analysis outlined in Resnjanskij et al. (2021) based on Heckman, Pinto, and Savelyev (2013), which is why the negative mediator is removed before estimating the final analysis. Staying up to date and learning by doing are, thus, the two knowledge diffusion aspects that are included in the mediation. The final mediator is a numeracy skill measure from the PIAAC test. It is necessary to include all relevant mediators for the mediation results to be valid. Since both a strong individualism effect on cognitive skills (Hartinger et al. 2021) and the wage returns to skills (Hanushek et al. 2015) are well documented, including numeracy as a mediator is of first-order importance.

Together with equation (1), equations (3) and (4) formalize the mediation approach for k mediators M_{ido}^{k}:

$$Log(Wage)_{ido} = \alpha_0 + \alpha_1 \overline{IDV_o} + \boldsymbol{X}'_{ido}\boldsymbol{\omega} + \vartheta_d + C_o + \varphi_{ido}. \tag{3}$$

$$Log(Wage)_{ido} = \alpha_0 + \alpha_1^{res} \overline{IDV_o} + \sum_k \theta^k M_{ido}^{k} + \boldsymbol{X}'_{ido}\boldsymbol{\omega} + \vartheta_d + C_o + v_{ido}. \tag{4}$$

Here, α_1^{res} captures the individualism effect on productivity that does not run through the set of mediators. Aside from determining the share of the individualism effect on productivity that runs through all mediators combined ($1 - \alpha_1^{res}/\alpha_1$), assessing the *relative* importance of each respective mechanism is a key goal of the mediation analysis. This exercise is particularly important, since one of the included mediators (numeracy skills) is outside the focus of this study and mainly included for validity reasons. The relative contributions are estimated as follows:

(5) $$Relative\ contribution\ M_k = \theta^k\ \beta_1^k / \alpha_1.$$

Here, β_1^k is the coefficient from the regression of the respective mediator on individualism (and controls) from Table 1 and Table 2 following equation (1).

Naturally, the mediation set-up comes with a specific set of validity assumptions (Heckman, Pinto, and Savelyev 2013; Heckman and Pinto 2015; Resnjanskij et al. 2021): First, as illustrated by equation (4), the mediation assumes that individual productivity can be estimated as a *linear combination* of the individualism-induced mediators (plus control variables and fixed effects). Unobserved mediators in the error term are assumed to be uncorrelated with the mediators of interest and controls. Applied to this context, the assumptions of the approach call for a causal effect of 1) individualism on wages, 2) individualism on the mediators, and 3) the mediators on productivity. The first effect is estimated in Table 4. The second effect is established in Section V of this paper. Despite the limitations of the epidemiological approach and the absence of truly (quasi-)experimental variation, the estimated relationships between individualism and innovation-conducive behaviors are strong and robust. Finally, the causal effect of the mediators on productivity is the most critical assumption behind this mediation analysis. Unlike the individualism effects, the relationship between the mediators and productivity is estimated as a simple correlation with basic controls and fixed effects in this study since the epidemiological approach cannot be applied to this part of the analysis. This is a drawback since causality can hardly be argued for. A helpful remedy would be a comparison of the coefficients in this study with truly causal estimations from the literature.

While regional analyses do find significant relationships between innovative occupational structure and wages (Florida 2002; Florida, Mellander, and Stolarick 2008), individual-level evidence on the causal effect of innovative occupations on wages is not readily available.[20] The mediation analysis is informative about the relative contributions of different innovation-conducive behaviors to the overall productivity effect of individualism, but it must be noted that possibly not all assumptions behind the approach are fulfilled. The analysis, thus, leaves scope for future research.

[20] Note that Florida's region-level analyses are not undisputed. For instance, Donegan et al. (2008) find that his measures do not outperform traditional measures of regional human capital. Recall, however, that it is not the purpose of this study is to draw a precise line between innovativeness and human capital but rather uncover connections between the two.

D. Controlling for Migrant Selection

D.1 PIAAC Data

Table D1. Individualism and Job Selection—Controlling for Migration Costs

	Full Sample					Self-employed
	Creative Occupation	Bohemian	Artist	Research	Self-employed	Research
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.068***	0.017***	0.007***	0.028***	0.014*	0.042***
	(0.018)	(0.004)	(0.002)	(0.005)	(0.008)	(0.016)
Educational selection	-0.000	-0.000	0.000	0.000	0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Geographic distance	0.012**	-0.003*	-0.000	0.001	0.011***	-0.000
	(0.006)	(0.002)	(0.001)	(0.003)	(0.003)	(0.008)
Contiguity	0.006	-0.012*	0.003	-0.031**	-0.022	-0.041
	(0.034)	(0.007)	(0.003)	(0.014)	(0.017)	(0.033)
Linguistic proximity	0.124*	0.043*	-0.031	0.005	-0.097	0.054
	(0.070)	(0.025)	(0.019)	(0.037)	(0.062)	(0.129)
Genetic distance	0.006	-0.001	-0.005	0.006	-0.031**	-0.015
	(0.025)	(0.005)	(0.003)	(0.015)	(0.014)	(0.039)
Inequality distance	0.004***	0.000	0.000	0.002**	-0.001	0.001
	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.43	0.03	0.01	0.11	0.14	0.12
R-squared	0.13	0.04	0.02	0.05	0.06	0.10
Origins	66	66	66	66	66	56
Observations	4,550	4,550	4,550	4,550	4,550	618

Notes: The table shows the results for the outcome indicated in the column header in the sample of first-generation migrants. Observations are weighted, giving each destination country the same weight. Individualism refers to Hofstede's index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. See text for the definition of further variables. Missing observations in the selection variables are imputed by the international mean (at the country level). *Covariates*: age, age squared and a gender dummy. *Fixed effects:* destination country and continent of origin country. Standard errors clustered at the origin-country level reported in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: PIAAC, Hofstede (2001), CEPII (Mayer and Zignago 2011), Krieger, Renner, and Ruhose (2018), Brücker, Capuano, and Marfouk (2013), Hartinger et al. (2021).

Table D2. Individualism and Knowledge Diffusion—Controlling for Migration Costs

	Between-occupation			Within-occupation		
	Keeping up to date	Learning by doing	Learning from coworkers	Keeping up to date	Learning by doing	Learning from coworkers
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.077**	0.069***	0.069***	0.040	0.028	0.031*
	(0.033)	(0.023)	(0.021)	(0.025)	(0.018)	(0.016)
Educational selection	-0.000	-0.001	-0.002	-0.000	-0.001	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Geographic distance	0.008	0.009	0.014	0.001	0.006	0.011
	(0.011)	(0.012)	(0.009)	(0.010)	(0.013)	(0.009)
Contiguity	0.078	-0.027	0.040	0.053	-0.041	0.018
	(0.068)	(0.048)	(0.050)	(0.052)	(0.040)	(0.037)
Linguistic proximity	0.350**	0.114	0.152	0.259*	0.059	0.046
	(0.171)	(0.173)	(0.147)	(0.136)	(0.182)	(0.157)
Genetic distance	0.070	0.022	0.009	0.079*	0.022	0.005
	(0.053)	(0.053)	(0.049)	(0.043)	(0.053)	(0.045)
Inequality distance	0.011***	0.004**	0.002	0.008***	0.002	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
2-Digit Occupation				Yes	Yes	Yes
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.05	0.04	0.05	0.14	0.10	0.13
Origins	66	66	66	66	66	66
Observations	4,175	4,175	4,175	4,175	4,175	4,175

Notes: The table shows the results for the outcome indicated in the column header in the sample of first-generation migrants. Observations are weighted, giving each destination country the same weight. Individualism refers to Hofstede's index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. See text for the definition of further variables. Missing observations in the selection variables are imputed by the international mean (at the country level). *Covariates*: age, age squared and a gender dummy. *Fixed effects:* destination country and continent of origin; 2-digit ISCO-08 occupation in Columns (4)-(6). Standard errors clustered at the origin-country level reported in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: PIAAC, Hofstede (2001), CEPII (Mayer and Zignago 2011), Krieger, Renner, and Ruhose (2018), Brücker, Capuano, and Marfouk (2013), Hartinger et al. (2021).

Table D3. Individualism and Job Selection—Controlling for Origin Country Characteristics

	Full Sample					Self-employed
	Creative Occupation	Bohemian	Artist	Research	Self-employed	Research
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.077***	0.015***	0.007***	0.031***	0.013	0.039**
	(0.023)	(0.004)	(0.002)	(0.010)	(0.009)	(0.016)
Share Tertiary	-0.002	0.001	-0.001	0.002*	-0.002	-0.000
	(0.003)	(0.001)	(0.000)	(0.001)	(0.002)	(0.004)
Log GDP	-0.019	0.006	0.003*	-0.008	-0.007	0.006
	(0.025)	(0.004)	(0.002)	(0.010)	(0.008)	(0.024)
Patents	0.015*	0.001	0.000	-0.002	0.005	0.005
	(0.007)	(0.002)	(0.001)	(0.003)	(0.004)	(0.007)
Long-term Orientation	0.015	0.000	-0.000	0.010**	0.017*	0.019
	(0.015)	(0.003)	(0.001)	(0.005)	(0.009)	(0.014)
Uncertainty Avoidance	0.004	0.002	0.001	0.001	-0.002	0.011
	(0.018)	(0.004)	(0.002)	(0.007)	(0.007)	(0.013)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.43	0.03	0.01	0.11	0.14	0.12
R-squared	0.12	0.04	0.02	0.04	0.06	0.10
Origins	67	67	67	67	67	57
Observations	4,627	4,627	4,627	4,627	4,627	623

Notes: The table shows the results for the outcome indicated in the column header in the sample of first-generation migrants. Observations are weighted, giving each destination country the same weight. Individualism, long-term orientation, and uncertainty avoidance refer to the respective Hofstede index and are standardized to a mean of 0 and a standard deviation of 1 in the full international sample. See text for the definition of further variables. Missing observations in the origin-country variables are imputed by the international mean (at the country level). *Covariates*: age, age squared and a gender dummy. *Fixed effects:* destination country and continent of origin. Standard errors clustered at the origin-country level reported in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: PIAAC, Hofstede (2001), Penn World Table 9.0 (Feenstra, Inklaar, and Timmer 2015), Barro and Lee (1996), World Bank.

Table D4. Individualism and Knowledge Diffusion—Controlling for Origin-Country Characteristics

	Between-occupation			Within-occupation		
	Keeping up to date	Learning by doing	Learning from coworkers	Keeping up to date	Learning by doing	Learning from coworkers
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.131***	0.088**	0.041	0.079**	0.032	-0.012
	(0.044)	(0.033)	(0.030)	(0.034)	(0.028)	(0.023)
Share Tertiary	0.002	0.005	0.003	0.008*	0.009*	0.008**
	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
Log GDP	-0.102**	-0.059**	-0.010	-0.094***	-0.060**	-0.006
	(0.039)	(0.029)	(0.026)	(0.030)	(0.025)	(0.023)
Patents	0.011	0.023**	0.025	0.004	0.017**	0.017
	(0.012)	(0.010)	(0.018)	(0.008)	(0.008)	(0.014)
Long-term Orientation	-0.013	-0.023	-0.005	-0.023	-0.030	-0.014
	(0.035)	(0.025)	(0.025)	(0.032)	(0.026)	(0.026)
Uncertainty Avoidance	0.003	0.020	-0.023	0.007	0.013	-0.028
	(0.042)	(0.026)	(0.025)	(0.030)	(0.023)	(0.024)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
2-Digit Occupation				Yes	Yes	Yes
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.05	0.04	0.06	0.14	0.11	0.13
Origins	67	67	67	67	67	67
Observations	4,250	4,250	4,250	4,250	4,250	4,250

Notes: The table shows the results for the outcome indicated in the column header in the sample of first-generation migrants. Observations are weighted, giving each destination country the same weight. Individualism, long-term orientation, and uncertainty avoidance refer to the respective Hofstede index and are standardized to a mean of 0 and a standard deviation of 1 in the full international sample. See text for the definition of further variables. Missing observations in the origin-country variables are imputed by the international mean (at the country level). *Covariates*: age, age squared and a gender dummy. *Fixed effects:* destination country and continent of origin. Standard errors clustered at the origin-country level reported in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: PIAAC, Hofstede (2001), Penn World Table 9.0 (Feenstra, Inklaar, and Timmer 2015), Barro and Lee (1996), World Bank.

D.2 Patent Data

Table D5. Individualism and Patenting—Controlling for Migration Costs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Individualism	1.143***	1.014***	0.987***	1.099***	1.027***	1.083***	1.015***
	(0.269)	(0.309)	(0.339)	(0.279)	(0.227)	(0.275)	(0.251)
Educational selection	0.038***						0.040***
	(0.012)						(0.011)
Geographic distance		-0.092***					-0.042
		(0.036)					(0.058)
Contiguity			1.709***				1.548***
			(0.319)				(0.318)
Linguistic proximity				-2.600**			-1.440
				(1.082)			(0.961)
Genetic distance					-0.239		-0.150
					(0.403)		(0.448)
Inequality distance						0.001	-0.020
						(0.025)	(0.019)
Fixed Effects							
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Destination	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.69	0.68	0.71	0.68	0.67	0.67	0.73
Origins	68	68	68	68	68	68	68
Observations	53,502	53,502	53,502	53,502	53,502	53,502	53,502

Notes: The table shows the results for the number of patents filed per year based on the aggregate epidemiological approach. Hofstede IDV refers to Hofstede's individualism index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. See Appendix B for the definition of further variables. Missing observations in the country(-pair) variables are imputed by the country(-pair) mean of all available countries with a Hofstede individualism score in the main sample (by year for time-varying variables. *Fixed Effects: Destination* refers to the inventors' country of residence. *Year* refers to the patent's priority year, which is the year the patent is first filed anywhere. *Origin continent* refers to the continent of the inventors' origin country. *Origins* refer to the number of origin countries. Standard errors clustered at the origin-country level reported in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: Miguélez and Fink (2013), Hofstede (2001), CEPII (Mayer and Zignago 2011), Krieger, Renner, and Ruhose (2018), Brücker, Capuano, and Marfouk (2013), Hartinger et al. (2021).

Table D6. Individualism and Patenting—Origin-Country Controls

	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	1.395***	1.109***	0.324	1.165***	1.028***	0.470*
	(0.260)	(0.278)	(0.201)	(0.279)	(0.283)	(0.248)
Share Tertiary	-0.068**					-0.018
	(0.033)					(0.022)
TFP		-2.962				-1.338
		(1.882)				(0.894)
Log(GDP)			0.918***			0.770***
			(0.120)			(0.105)
Long-term Orientation				0.514**		0.239*
				(0.230)		(0.137)
Uncertainty Avoidance					-0.282	-0.287***
					(0.215)	(0.081)
Fixed Effects						
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Year x Destination	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	8.26	8.26	8.26	8.26	8.26	8.26
Pseudo R-squared	0.69	0.68	0.82	0.70	0.68	0.84
Origins	68	68	68	68	68	68
Observations	53,502	53,502	53,502	53,502	53,502	53,502

Notes: The table shows the Poisson results for the number of patents filed per year. The results are based on the full sample of migrant inventors. Individualism, long-term orientation, and uncertainty avoidance refer to the respective Hofstede indices. All measures of culture are standardized to a mean of 0 and a standard deviation of 1 in the full international sample. See text for the definition of further variables. Missing observations in the country-of-origin variables are imputed by the mean of all available countries with a Hofstede individualism score in the main sample (by year for time-varying variables). *Fixed Effects: Destination* refers to the inventors' country of residence. *Year* refers to the patent's priority year, which is the year the patent is first filed anywhere. *Origin continent* refers to the continent of the inventors' origin country. *Origins* refer to the number of origin countries. Standard errors clustered at the origin-country level reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PCT, Miguélez and Fink (2013), Penn World Table 9.0 (Feenstra, Inklaar, and Timmer 2015), Barro and Lee (1996), Hofstede (2001).

E. Additional Robustness Checks

E.1 PIAAC Data

Table E1. Individualism and Job Selection—Specification Checks

	Full Sample					Self-employed
	Creative Occupation	Bohemian	Artist	Research	Self-employed	Research
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.066***	0.016***	0.005**	0.023***	0.003	0.042
	(0.021)	(0.004)	(0.002)	(0.009)	(0.008)	(0.027)
Age	0.018***	-0.000	0.000	0.003	0.003	-0.002
	(0.005)	(0.002)	(0.001)	(0.002)	(0.004)	(0.018)
Age squared	-0.019***	0.000	-0.001	-0.004	0.001	0.004
	(0.006)	(0.002)	(0.001)	(0.003)	(0.005)	(0.022)
Female	-0.073**	0.001	0.006**	-0.061***	-0.034***	0.012
	(0.028)	(0.005)	(0.002)	(0.019)	(0.012)	(0.056)
Fixed Effects						
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Year of Migration	Yes	Yes	Yes	Yes	Yes	Yes
Year x Destination	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.43	0.03	0.01	0.11	0.13	0.12
R-squared	0.27	0.25	0.26	0.17	0.23	0.66
Origins	66	66	66	66	66	57
Observations	4,280	4,280	4,280	4,280	4,280	570

Notes: The table shows the results for the outcome indicated in the column header in the sample of first-generation migrants. Observations are weighted, giving each destination country the same weight. The sample is restricted to destination countries with at least 100 migrant observations with a Hofstede individualism score from at least 10 different origins following Hartinger et al. (2021). Individualism refers to Hofstede's index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Fixed effects:* year-of-migration-specific destination country fixed effects and continent of origin country. Standard errors clustered at the origin-country level reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PIAAC, Hofstede (2001).

Table E2. Individualism and Knowledge Diffusion—Specification Checks

	Between-occupation			Within-occupation		
	Keeping up to date	Learning by doing	Learning from coworkers	Keeping up to date	Learning by doing	Learning from coworkers
	(1)	(2)	(3)	(5)	(4)	(6)
Individualism	0.119**	0.106***	0.090***	0.076**	0.064***	0.048**
	(0.045)	(0.027)	(0.026)	(0.032)	(0.021)	(0.021)
Age	0.022**	-0.017	-0.011	0.015	-0.025**	-0.021
	(0.009)	(0.012)	(0.015)	(0.009)	(0.011)	(0.014)
Age squared	-0.034***	0.008	-0.001	-0.021*	0.018	0.012
	(0.011)	(0.015)	(0.017)	(0.011)	(0.014)	(0.017)
Female	-0.112***	-0.068*	-0.049	-0.087***	-0.027	0.025
	(0.034)	(0.038)	(0.035)	(0.031)	(0.038)	(0.035)
Fixed Effects						
2-Digit Occupation				Yes	Yes	Yes
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Year of Migration	Yes	Yes	Yes	Yes	Yes	Yes
Year x Destination	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.21	0.21	0.22	0.28	0.27	0.29
Origins	66	66	66	66	66	66
Observations	3,942	3,942	3,942	3,942	3,942	3,942

Notes. The table shows the results for the outcome indicated in the column header in the sample of first-generation migrants. Observations are weighted, giving each destination country the same weight. The sample is restricted to destination countries with at least 100 migrant observations with a Hofstede individualism score from at least 10 different origins following Hartinger et al. (2021). Individualism refers to Hofstede's index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Fixed effects:* year-of-migration-specific destination country fixed effects and continent of origin country, and 2-digit occupation in Columns (4)-(6). Standard errors clustered at the origin-country level reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PIAAC, Hofstede (2001).

Table E3. Person-Level Individualism and Innovation Behaviors—Broad Index (Natives)

	Creative Occupation	Research Occupation	Self-employed	Keeping up to date
	(1)	(2)	(3)	(4)
Individualism	0.178***	0.043***	0.060***	0.379***
	(0.008)	(0.003)	(0.004)	(0.013)
Age	0.020***	0.003***	0.001	-0.007***
	(0.002)	(0.001)	(0.001)	(0.002)
Age squared	-0.022***	-0.004***	0.004**	0.003
	(0.002)	(0.001)	(0.002)	(0.003)
Female	0.027**	-0.023***	-0.052***	0.056***
	(0.012)	(0.002)	(0.009)	(0.010)
Fixed Effects				
Destination Country	Yes	Yes	Yes	Yes
R-squared	0.15	0.03	0.12	0.16
Observations	99,144	99,144	99,144	99,144

Notes: The table shows the results for the outcomes indicated in the column header in the sample of natives. Observations are weighted, giving each destination country the same weight. Individualism refers to the broad personal individualism index developed in Hartinger et al. (2021) and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Fixed effects:* country. Standard errors reported in parentheses are heteroskedasticity-robust.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PIAAC.

Table E4. Person-Level Individualism and Job Selection—Full Results for Natives

	Full Sample					Self-employed
	Creative Occupation	Bohemian	Artist	Research	Self-employed	Research
	(1)	(2)	(3)	(4)	(5)	(6)
Individualism	0.116***	0.008***	0.002***	0.032***	0.008***	0.035***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.36	0.02	0.00	0.07	0.18	0.07
R-squared	0.11	0.01	0.00	0.03	0.10	0.04
Observations	99,343	99,343	99,343	99,343	99,343	17,905

Notes: The table shows the results for the outcomes indicated in the column header in the sample of natives. Observations are weighted, giving each destination country the same weight. Individualism refers to the private-life-based personal individualism index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Covariates*: age, age squared, and a gender dummy. *Fixed effects:* country. Standard errors reported in parentheses are heteroskedasticity-robust.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: PIAAC.

Table E5. Person-Level Individualism and Knowledge Diffusion—Full Results for Natives

	Between-occupation			Within-occupation		
	Keeping up to date	Learning by doing	Learning from coworkers	Keeping up to date	Learning by doing	Learning from coworkers
	(1)	(2)	(3)	(5)	(4)	(6)
Individualism	0.204***	0.179***	0.175***	0.146***	0.134***	0.125***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Fixed Effects						
2-Digit Occupation				Yes	Yes	Yes
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.10	0.11	0.10	0.16	0.14	0.13
Observations	88,596	88,596	88,596	88,596	88,596	88,596

Notes: The table shows the results for the outcomes indicated in the column header in the sample of natives. Observations are weighted, giving each destination country the same weight. Individualism refers to the private-life-based personal individualism index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Covariates*: age, age squared, and a gender dummy. *Fixed effects:* country. Standard errors reported in parentheses are heteroskedasticity-robust.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: PIAAC.

E.2 Patent Data

Table E6. Individualism and Patents—Different Samples

	Unrestricted Sample	Hofstede destinations	Dest. w. 1000 or more patents	Excl. top patenting origins	2004 – 2011
	(1)	(2)	(3)	(4)	(5)
Individualism	1.145***	1.085***	1.088***	1.063***	1.038***
	(0.299)	(0.294)	(0.298)	(0.138)	(0.296)
Fixed Effects					
Destination Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Year x Destination	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes
Outcome mean	3.63	9.14	11.87	4.57	18.21
Pseudo R-squared	0.73	0.67	0.65	0.67	0.64
Origins	68	68	68	62	68
Observations	121,755	47,923	36,469	43,196	16,498

Notes: The table shows the results for the number of patents filed per year based on the aggregate epidemiological approach for different samples. Column (1) shows the result for the entirely unrestricted sample and Column (2) for the sample of origin *and destination* countries for which a Hofstede individualism score is available. Column (3) focuses on 23 top patenting destination countries with more than 1,000 migrant patents in total, while Column (4) excludes the six origin countries that reach patent counts of more than 1,000 patents per destination country per year at least once (Canada, China, Germany, the United Kingdom, India, and Korea). Column (5) is restricted to the years 2004-2011 which offer the best data quality according to Miguélez and Fink (2013). Hofstede IDV refers to Hofstede's individualism index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Fixed Effects: Destination* refers to the inventors' country of residence. *Year* refers to the patent's priority year, which is the year the patent is first filed anywhere. *Origin continent* refers to the continent of the inventors' origin country. *Origins* refer to the number of origin countries. Standard errors clustered at the origin-country level reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: Miguélez and Fink (2013), Hofstede (2001).

Table E7. Individualism and Patents—Cross-Section Results for 2011

	Non-zero Observations	Count Data		
	(1)	(2)	(3)	(4)
	OLS	Logit	Neg. Bin.	Poisson
Individualism	26.972***	0.762***	0.960***	1.008***
	(7.472)	(0.119)	(0.101)	(0.281)
Ln(alpha)			0.855***	
			(0.085)	
Fixed Effects				
Destination	Yes	Yes	Yes	Yes
Year				
Year x Destination				
Origin Continent	Yes	Yes	Yes	Yes
Outcome mean	32.98	18.29	18.25	18.27
(Pseudo) R-squared	0.12	0.23	0.15	0.63
Origins	66	68	68	68
Observations	1,130	2,039	2,044	2,041

Notes: The table abstracts from the longitudinal character of the data by showing the result for the most recent year with high data quality, 2011. This reduces the number of fixed effects drastically and allows for a more accurate use of logit and negative binomial models. Column (1) shows OLS results only for origin-destination pairs with at least one patent in 2011. Columns (2)-(4) summarize logit, negative binomial, and Poisson results for the full 2011 sample; slight discrepancies in sample size are due to technical reasons (such as the omission of singletons in the Poisson regression). Hofstede IDV refers to Hofstede's individualism index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Fixed Effects: Destination* refers to the inventors' country of residence. *Year* refers to the patent's priority year, which is the year the patent is first filed anywhere. *Origin continent* refers to the continent of the inventors' origin country. *Origins* refer to the number of origin countries. Standard errors clustered at the origin-country level reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Data sources: Miguélez and Fink (2013), Hofstede (2001).

Table E8. Individualism and Patents—Specification Checks

	5-Year Moving Average	Controlling for Origin Inventor Diaspora	Destination-Clustered	Origin-Destination-Clustered	Twoway Clustered Origin & Destination	Origin--Year-Clustered	Heteroskedasticity Robust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Individualism	1.083***	0.692***	1.084***	1.084***	1.084***	1.084***	1.084***
	(0.292)	(0.083)	(0.051)	(0.236)	(0.178)	(0.079)	(0.065)
Diaspora 2010 / 1000		0.071***					
		(0.004)					
Fixed Effects							
Destination Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Destination	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	8.39	8.26	8.26	8.26	8.26	8.26	8.26
Pseudo R-squared	0.67	0.84	0.67	0.67	0.67	0.67	0.67
Clusters	68	68	118	2,209	68 (orig.) 118 (dest.)	2,242	
Observations	53,502	53,502	53,502	53,502	53,502	53,502	53,502

Notes: The table shows the results for the number of patents filed per year based on the aggregate epidemiological approach for several additional specification changes. Column (1) measures patents as the moving five-year average count (for the first and last periods of the panel, a shortened version of the moving average is used). Column (2) controls for the inventor diaspora (2001-2010) of the origin country following Miguélez and Fink (2013). Column (3) clusters standard errors at the destination-country level, Column (4) at the destination-origin-interaction level, Column (5) uses twoway clustering at the origin and destination level, Column (5) clusters at the origin-year interaction level, and Column (6) uses simple heteroskedasticity-robust standard errors. Hofstede IDV refers to Hofstede's individualism index and is standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Fixed Effects: Destination* refers to the inventors' country of residence. *Year* refers to the patent's priority year, which is the year the patent is first filed anywhere. *Origin continent* refers to the continent of the inventors' origin country. *Origins* refer to the number of origin countries.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: Miguélez and Fink (2013), Hofstede (2001).

Table E9. Individualism and Patents—Alternative Individualism-Collectivism Measures

	(1)	(2)	(3)	(4)
Schwartz Affective Autonomy	1.174***			
	(0.235)			
Schwartz Intellectual Autonomy		0.754***		
		(0.236)		
Schwartz Embeddedness			-1.276***	
			(0.261)	
Globe In-group Collectivism				-0.346*
				(0.199)
Fixed Effects				
Destination	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Year x Destination	Yes	Yes	Yes	Yes
Origin Continent	Yes	Yes	Yes	Yes
Outcome mean	8.11	8.11	8.11	9.30
(Pseudo) R-squared	0.67	0.63	0.69	0.63
Origins	72	72	72	57
Observations	53,872	53,872	53,872	45,597

Notes: The table shows the results for the number of patents filed per year based on the aggregate epidemiological approach for several alternative individualism-collectivism measures. Main results for the PIAAC-based analyses are similarly robust but omitted for expositional reasons due to the large number of measure-outcome permutations. The Schwartz autonomy measures capture individualism, while the embeddedness measure as well as the Globe measure capture collectivism – a negative sign is, thus, expected for the latter two coefficients. To fully exploit the natural variation in origin countries based on the availability of each measure and to avoid introducing artificial measurement error, the measures are not imputed nor restricted to match the main estimation sample. All IDV-COL measures are standardized to a mean of 0 and a standard deviation of 1 in the full international sample. *Fixed Effects: Destination* refers to the inventors' country of residence. *Year* refers to the patent's priority year, which is the year the patent is first filed anywhere. *Origin continent* refers to the continent of the inventors' origin country. *Origins* refer to the number of origin countries. Standard errors clustered at the origin-country level reported in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: Miguélez and Fink (2013), Schwartz (1994), House (2004).