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The Wealth of (Open Data) Nations? Examining the Interplay of Open Government Data and Country-level Institutions for Entrepreneurial Activity at the Country-level

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The Wealth of (Open Data) Nations?

Examining the Interplay of Open Government Data and Country-level Institutions for Entrepreneurial Activity at the Country-level

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Abstract

The provision of Open Data (OD) has been promoted by governments around the world with the hope of fuelling entrepreneurial use of the data for new products or process innovations. However, these benefits are still far from being fully understood and realised, and it remains unclear to what extent OD leads to systematic benefits for entrepreneurship. This paper aims to shed light to this open question by providing novel empirical evidence on the relationship between OD publishing and entrepreneurial outcomes at country-level. We draw upon a longitudinal dataset comprising 90 countries observed over the period 2013-2016. We find a significant and positive association between OD adoption and entrepreneurship at the country-level. The results also show that OD adoption and entrepreneurship is strong in countries with high institutional quality. We argue that unless a country has quality institutions, publishing OD alone does not positively affect entrepreneurship for the digital economy. Publishing OD is not sufficient to improve entrepreneurship alone, so states need to move beyond a focus on OD initiatives and promotion, to focus on a broader set of policy initiatives that promote good governance.

Keywords: open data; open government data; institutions; entrepreneurship; country-context; digital economy

JEL codes: O33, O36, O43, L26

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1 INTRODUCTION

Data has been highlighted as 'the new oil' for the digital economy (Matsakis, 2019; Parkins, 2017; Dance et al., 2018). Within this context, the provision of Open Data (OD) has been promoted by governments around the world with the hope of fuelling entrepreneurial use of the data for new product or process innovations (Janssen et al. 2015; Hughes-Cromwick and Coronado 2019). OD refers to information that has been collected by an organisation (usually a public administration) which owns the IP rights, but which is then published online for other organisations and entrepreneurs to use freely (Open Data Institute 2014). What is especially notable is how OD has to be made available at no cost, and which can be used by any organisation (Open Data Institute 2014). Advocates of the Open Data Movement claim that it reduces costs (as it is free), and enables entrepreneurs to retain more monetary value from new innovations, while providing access to previously unavailable data (Lee et al. 2014; BIS 2014; Magalhaes and Roseira 2017). Advocates have also claimed that OD has the potential to advance entrepreneurial activities (Huijboom and Van den Broek 2011). OD provides the information needed for the identification of new business opportunities, strategic planning and the evaluation of investment projects (Bonina, 2013), in addition to being a core input to innovations (Lee et al. 2014; Hughes-Cromwick and Coronado 2019). However, these benefits are still far from being fully understood and realised, and it remains unclear to what extent OD leads to systematic benefits for entrepreneurship (Lee et al. 2014; Almirall 2015; Huber et al. 2020).

This paper aims to shed light on these open questions by providing novel empirical evidence on the relationship between OD publishing and entrepreneurial outcomes at country-level. We draw upon a longitudinal dataset comprising 90 countries observed over the period 2013-2016. Our results provide novel support for the argument that OD is beneficial for entrepreneurship. Overall, there is a significant and positive association between OD adoption and country-level entrepreneurship. The results also show that OD adoption and entrepreneurship is strong in countries with high institutional quality. We argue that unless a country has quality institutions, publishing OD alone does not positively affect entrepreneurship for the digital economy. Publishing OD is not sufficient to improve entrepreneurship alone, so state institutions need to move beyond a focus on OD initiatives and promotion, to focus on a broader set of policy initiatives that promote good governance.

This paper is structured as follows. Section 2 provides a review of the extant literature and the main research questions. Section 3 discusses the data and methodology, and Section 4 the results. Section 5 concludes the paper.

2 LITERATURE REVIEW AND RESEARCH QUESTIONS

Open data in the digital economy

Researchers and policy-makers have long recognised the role of entrepreneurs in job creation, innovation and economic growth within national economies (Baumol 2002; Wolf and Pett, 2006; Acs et al. 2014; Urbano et al. 2019). More recently, both researchers and policy-makers alike have come to view data-driven start-ups as having the potential to disrupt existing markets and to create new economic and social value (Bogers et al. 2017; Dodgson et al., 2006; Huber, 2013; Whelan et al., 2010). Data has been viewed as a 'raw material' or 'the new oil' for the digital economy, with scholars becoming interested in topics such as 'big data' (Chen and Zhang, 2014) and 'linked data' (Wood, 2010). One particular phenomenon within the field of the digital economy, which so far remains understudied is the concept of open data (OD) (Huber et al. 2020).

OD is published by public and private sector organisations online and in machine-readable format, but is unique in that it is licensed for everybody to use and republish without financial costs (Open Data Institute 2015). For entrepreneurs in the digital economy, OD offers substantial potential, by avoiding the costs of acquiring proprietary data, and using it to create new value-added applications and services, overcoming resource constraints (Chan, 2013; Janssen, 2011; Lee et al., 2014; Eftekhari and Bogers, 2016; Nagaraj 2016). Furthermore, the publication of data by government agencies offers entrepreneurs new opportunities, through the release of data that was not previously available (Magalhaes and Roseira 2017).

It is difficult to determine the exact beginning of the Open Data Movement, but in 2009 the US government launched the Memorandum on Transparency and Open Government to make more government data public (Lee et al. 2014). European and emerging economy governments have also begun to publish OD, in addition to private sector organizations, partly to enhance transparency through open government data (Bates 2011), but more recently to also provide data-driven opportunities for entrepreneurs (Lindman and Nyman 2014; Corrales-Garay et al. 2019). OD can cover different themes at different scales, from the local to the global. It encompasses activities such as transportation, location based services, property, education, health and meteorological activities. Policymakers are paying increased attention to the potential role of the OD in boosting entrepreneurship and innovation within the digital economy (Cabinet Office 2012; Open Data Institute 2015; Lee et al. 2014; Almirall 2015; Chattapadhyay 2013; dos Santos Brito 2014; Hughes-Cromwick and Coronado 2019).

While there is a burgeoning range of case studies and anecdotal evidence concerning the successful use of OD by entrepreneurs, it remains unclear to what extent OD systematically leads to positive entrepreneurial outcomes (Lee et al. 2014; Almirall 2015; Huber et al. 2020). For example, Corrales-Garay et al. (2019) argue that OD can add $900 billion to the global economy, while Tinholt (2013) calculated that the annual economic aggregate impact from apps based on OD across the EU17 is €140 billion.

While these headline statistics make for positive reading, the current body of research is underdeveloped, with a notable absence of wider systematic study, or deeper understanding into the mechanisms that lead to positive entrepreneurial outcomes. For instance, many earlier papers from the OD literature are conceptual (Jaeger and Grimes 2010; McDermott 2010) or examine the design of OD ecosystems (Charalabidis et al 2011). In addition, the literature has been largely exploratory (Janssen et al. 2015), with research often focussing on qualitative methods or case study approaches, at the sectoral or country-level (Corrales-Garay et al. 2019). In contrast, there are a limited number of quantitative studies, with a particular dearth of research on the cross-comparative aspects of OD, with the exception of consultancy and practitioner reports, such as the above, which are mostly descriptive (e.g. Tinholt 2013). While research on the public sector has often focussed on the risks, advantages and barriers of OD publication, it has often overlooked relationships with user communities and entrepreneurs (Huber et al. 2020). There are many benefits advanced by proponents of OD to justify its publication, including a boost to economic growth, job creation, innovation and the development of transparency, but Huijboom and Van den Broek (2011) argue that evidence of the precise effects are often lacking.

As such, we argue that a cross-comparative, macro-level and quantitative study will make a novel contribution to research on OD, particularly on how OD affects entrepreneurship, and how this relationship is moderated by country-level institutions.

Mechanisms linking OD to entrepreneurial activity

2.1.1 The association between OD and entrepreneurship

OD has been recognised for its positive effect on business and product development. For example, Magalhaes and Roseira (2017) highlight how OD assists businesses in undertaking market analysis, process optimisation, product and service development, and R&D. More specifically, OD has been shown to be particularly important in supporting new firm creation and product development (Tinholt 2013; Huijboom and Van den Broek 2011; Huber et al. 2020). There are several mechanisms that enable OD to support new firm creation. First, OD facilitates the creation of novel products and services that are exclusively reliant on OD (Chan 2013). OD consists of diverse and often large datasets that were not previously available, particularly sources of government OD (Magalhaes and Roseira 2017; Nagaraj 2016), which enables the creation of new through innovation (Hughes-Cromwick and Coronardo 2019). Second, digitally focussed start-ups are reliant on data for their innovation. The costs of proprietary data can be high, which can create a barrier to new firm creation (Berends et al. 2017). The availability of OD can remove cost barriers to resource constrained firms, supporting firm formation. Third, a related mechanism centres on price reduction. The use of freely available OD can reduce costs for start-up services. Easily discoverable OD that can be accessed for free, where the data is harmonised, reduces administrative burdens and time costs, for new ventures improving efficiency (Estermann 2014; Berends et al. 2017). App pricing may not be financially viable, or desirable to consumers, if using expensive proprietary data, as this may increase costs of products to end users. The use of OD can reduce costs, making new digital apps and services financially viable. Fourth, access to OD can increase experimentation capacity for new ventures, enhancing innovation. As OD is freely available, resource constrained, new ventures are able to develop different prototypes of new services at low cost, without having to invest in proprietary data, which may not yield results (Huber at al. 2020). This enables new ventures to experiment widely using OD in the pursuit of new products and service development, while also potentially reducing nascent entrepreneurs' fear of failure (c.f Wennberg et al. 2013).

Despite the potential positive effect that OD has on new ventures, OD and its usefulness can vary in different dimensions. OD that is out of date, unreliable, and with availability constraints, can undermine its usefulness in innovation. In the following, we put forward three main mechanisms through which OD are expected to contribute to new firm formation at the country level: timeliness, source reliability and future availability.

OD timeliness

Timeliness links OD to entrepreneurship, the importance of which has been highlighted by researchers and practitioners, where timeliness refers to the how frequently OD is updated. OD can be published as a one-off static source of data as one snapshot in time, or it may be constantly undated in real-time through application programme interfaces (Huber et al. 2020).

OD that is newer and updated frequently has the potential to increase the capture of entrepreneurial opportunities (c.f. Tinholt 2013). First, if OD is published at a higher frequency, there is a larger volume of data. An abundance of OD can arguably contribute to the capture of opportunity recognition, as more OD can present more opportunities (Berends et al., 2017). Second, OD that is updated more frequently is likely to be more accurate providing a richer source of OD, with wider potential for wider uses. Tinholt (2013) note that granular data and depth is important, in addition to updating it regularly, an issue that 22% of countries overlook. Accurate and granular OD increases the potential of opportunity recognition and successful entrepreneurial orientation (cf. Davidsson 2015) due to potential for a wider range of application, in addition to increased abilities and aspirations, owing to the greater potential for product and service development as more accurate data has a wider variety of uses.

One example frequently highlighted in the literature is that of transport APIs, where real-time OD is made available by transport providers to third-party entrepreneurs, who create transport and navigation apps that use OD (Lindman and Nyman 2014). While static timetable OD could be useful, richer OD available in real-time can account for delays, enabling users to make better decisions on transport routes.

OD source reliability

Source reliability links OD to entrepreneurs and their ability to exploit data in new applications and services. While policy-makers may have previously focussed on the volume of OD published, scholars have highlighted the importance of information quality and in turn, the reliability of the data source (Lindman and Nyman 2014). This reliability is contingent on good governance of the OD publishing institutions (Huijboom and Van der Broek 2011)

In supporting entrepreneurs to capture opportunities using OD, better quality data provides opportunities to undertake more complex and niche tasks, with limited OD data functionality impeding commercialisation (Tinholt 2013). Poor quality OD cannot be used as widely, or there is limited information about the source quality and collection methods (Janssen et al. 2012). As such, OD following international standards and licensing can be used more easily by entrepreneurs and is more likely to be incorporated into new apps and services (Berends et al., 2017).

One particular example that relies upon data quality has involved the publication of geospatial OD (Nagaraj 2016). Location-based mobile apps are reliant on accurate data to assist users in navigation tasks. If OD geospatial data is inaccurate, it's unusable by entrepreneurs, who would instead have to purchase more expensive proprietary data. In this event, an app or service may not be cost effective. Alternatively, entrepreneurs may seek to experiment with new apps and services using OD (Janssen et al. 2012; Huber et al. 2020). If accurate data is not available, entrepreneurs may not experiment with a new service as they may not be able to afford proprietary data, or may discount a services as being unviable if the OD is inaccurate.

OD future availability

Future availability is a mechanism that links OD and entrepreneurship. OD needs to be sustained and entrepreneurs need to be confident that sources of OD will be available in the future (Lindman and Nyman 2014). As noted above, there can be variations in the frequency of OD publication, but OD sources can also be removed, or left unsupported.

If an entrepreneur is to develop an app or service around a source of OD, they need to be sure that the data will be available in the future (Berends et al. 2017). Even though OD is free, its exploitation requires the investment of resources. In the scenario where an OD source may not be available in the future, the entrepreneur may not develop the new app or service as it may fail if

OD is withdrawn, so new products and services are not created or opportunities captured (Huber et al. 2020). Concern over the future availability of data may be real, or perceived.

One particular example that relies on future OD availability concerns real-estate applications. Many apps enable citizens to view the availability of and quality of local amenities and services. OD on food inspections, health and education quality is often available (Janssen et al. 2012). Many of these apps collate OD for data on local services. If these sources of OD were discontinued, a central feature of home search functionality would be lost.

The above argument leads us to highlight our first research question relating to the relationship between the extent of OD adoption and the level of entrepreneurial activity in a country: *(1) what is the association between the adoption of OD and entrepreneurial activity at the country-level?*

2.1.2 The role of institutions on the relationship between OD and entrepreneurship

Country-level institutions may influence how OD publication affects entrepreneurial activity. The role of the state goes beyond simply publishing OD as an available asset, as they also affect the context within which entrepreneurial processes and outcomes occur (Huijboom and Van den Broek 2011; Lindman and Nyman 2014). For example, country-level institutions that protect intellectual property can help entrepreneurs to develop viable business models when using OD, or provide education, training and discovery support to assist entrepreneurs in innovating with OD (Corrales-Garay et al. 2019). Furthermore, countries with better governance are more likely to have government units that liaise with the users and entrepreneurs, to make sure that the three main OD characteristics (timeliness, source reliability and future availability) are adequately taken care of.

Recent literature has highlighted how studies of entrepreneurship have long overlooked the role of country-level institutions on entrepreneurial activity (Acs et al. 2014; Autio et al. 2014; Estrin 2013). Scholars have argued that studies have previously examined entrepreneurship at the individual cognitive-level (Shane and Venkataraman 2000) at the expense of the effect of country-level institutions,[1] or have acknowledged the influence of context (Aldrich and Fiol 1994; Welter 2011), but have still focussed on the individual-level creating a gap in the literature (Sorensen 2007; Zahra and Wright 2011). This underplays the role of how institutions regulate choices and behaviour (Davidsson 2006).

A dedicated research stream has examined how entrepreneurial activity is influenced by the institutional context (Estrin et al. 2013). Baumol (1990; 1993) identified how institutions create the structure of incentives that determine the choice of entry into entrepreneurship, while North (1990) argues that incentives for value adding behaviour depend on the quality of institutions. Furthermore, country-level institutional characteristics regulate resource allocation systems, which in turn determines individual opportunity pursuit (Acs et al. 2014).

While the notion that institutions are the ‘rules of the game’ (North, 1990) is widely utilised by scholars, there are a range of theoretical approaches. The role of institutional context has been conceptualised in various spatial scales. While we recognise the role of regional entrepreneurial eco-systems (Acs et al., 2017), this particular paper is concerned with the role of country-level institutions. In this paper, we understand institutional quality as country-level characteristics of governance levels regarding the implementation of rules supporting contractual relationships and market exchanges (Dau and Cuervo-Cazurra, 2004). This is centred on the topics of broad property rights and corruption (Woodruff, 2006), and high institutional quality means that the rule of law is applied and misbehaviour inhibited, where countries with the highest institutional quality have the best institutions (Sobel 2008).

As entrepreneurial behaviour is about mobilising and coordinating resources – such as OD – there is less insight into how variations in context – for example, quality of institutions – determine how

[1] Earlier exceptions have focussed on high tech clusters like Silicon Valley or Route 28 at the regional level (Acs et al. 2014)

easily resources can be mobilised and opportunities recognised, and in turn how this influences entrepreneurial activity (Autio et al. 2014). As entrepreneurial activity is shaped by country-level institutions, due to specific institutional configurations (Boettke and Coyne 2009; Sobel 2008; Estrin et al. 2013), differences in institutional quality will be likely to have an effect on (i) the quality and quantity of OD publishing and (ii) on the likelihood that OD as a raw material can be exploited by entrepreneurs.

Scholars have emphasised how good governance and leadership results in the publication of a greater volume of OD, but which is also of a better quality (Janssen et al. 2015; Lindman and Nyman 2014). Leadership and a responsibility for the publication of OD have been important for creating the infrastructure to publish quality OD (Berends et al. 2017). If leadership and good governance is absent, then it does not become a priority, leading to less data being published, which cannot then be used to create novel services and applications (Lindman and Nyman 2014). Studies have noted that in order to increase the publication of OD, formal policies are needed to steer government units into publishing OD (Huijboom and Van den Broek (2011). The ease of extraction of OD for external use is affected by institutional quality, where the development of clear OD standards, metadata, contextual information and licensing is important in enabling entrepreneurs to acquire OD (Dawes and Helbig 2010; Lindman and Nyman 2014). This raises the important question of whether institutional quality moderates the relationship between OD and entrepreneurship at the country-level. The following mechanisms may be underlying.

First, institutional quality may affect how OD affects opportunity recognition as low quality institutions undermine the institutional trust needed for entrepreneurship (Anokhin and Schulze, 2009; Hey and Trefethen 2005). A lack of trust in OD due to a low perception of the publishing quality institutions at the country-level may lead potential entrepreneurs to overlook opportunities. For instance, entrepreneurs may believe that OD published in a low quality institutional environment are not timely and reliable (c.f. Janssen et al. 2015). Also, a lack of trust in the public sector’s commitment to delivering a continuous stream of OD in the future may lead to lower levels of entrepreneurial activity, as future availability is important for returns to investment. Furthermore, these perceptions may lead to overestimating the risks; that is, even if entrepreneurs see an opportunity, they may reject and not pursue it (Cacciotti et al. 2016). These dimensions may be based on a low perception of trust in OD quality, even if the quality may be high as nascent entrepreneurship often rely on subjective perceptions (Arenius und Minniti, 2005).

Second, the dysfunctional effects of low quality of institutions on training and skill development may lead to lack of entrepreneurial abilities (c.f. Huber et al. 2020). That is, those dysfunctional effects may mean that there are fewer entrepreneurs with the ability to utilise publicly available OD for innovation as low quality institutions reduce the required capabilities in the digital economy (e.g. data science skills, for an overview of required skills see Open Data Institute, 2019).

Third, high quality institutions can facilitate the development of good relationships between government publishers of OD and the user community, for example through supported innovation contests (Juell-Skielse et al. 2014). This relationship improves and enhances the ability of entrepreneurs to realise the value of OD and to recognise opportunities that can be captured (c.f Zurada and Karwowski 2011). Countries with better governance and quality institutions appear to be more transparent and open to engaging with external innovation (c.f. Janssen et al. 2015). Transparent procedures and rules supporting contractual relationships and market exchanges make a development of a constructive relationship between OD publishers and OD users more likely.

Fourth, trust in the future availability of OD, trust in the rule of law including IP may affect entrepreneurial aspirations, by reducing a fear of failure (Cacciotti et al. 2016). For instance, corruption-related costs and risks may be a disincentive to invest in entrepreneurial growth (Dutta and Sobel, 2016).

In light of the above aspects, our study also attempts to investigate a second research question: *(2) Does the quality of institutions moderate the relationship between OD and entrepreneurship at the country-level?*

3 DATA DESCRIPTION AND METHOD

Data sources

The empirical analysis is based on a dataset that has been obtained by combining six different sources of country-level data: 1) The Global Entrepreneurship and Development Institute (GEDI) index; 2) The Open Data Barometer (ODB) score; 3) The Worldwide Governance Indicators (WGI) database; 4) The Global Competitiveness (GC) report; 5) The Economic Freedom (EF) index and 6) The Global Innovation (GI) index. The selection of these datasets is based on the aim of this work which is to measure the relationship between OD and entrepreneurship and the moderating role played by the quality of institutions.

The combination of these datasets ended-up with panel data structure, comprising 90 countries over the period 2013-2016. The restrictive time frame is due to the recent development of the OD movement and its formalisation in terms of data collection, release and comparison as an indicator at the country-level.

Measures and methods

3.1.1 Dependent variables and estimation method

As discussed in Section 1.2, we examine the relationship between OD and entrepreneurship at the country-level. Therefore, we estimate the following econometric model:

$$Entrepreneurship_{it} = \alpha + \beta_1 OpenData_{it} + \beta_2 InstQuality_{it} + \boldsymbol{x}'_{it}\theta + \eta_t + \mu_i + \varepsilon_{it}$$

where η_t is a series of year dummies; $\boldsymbol{x}'_{it}$ is a vector of country-specific control variables; μ_i indicates the country-specific unobserved heterogeneity term and ε_{it} is the usual error term. As we expect the strength of the relationship between open data and entrepreneurship to be affected by the institutional quality of the country, in a second specification we add the interaction between open data and institutional quality ($OpenData_{it}\ X\ InstQual_{it}$).

We adopt different specifications of our panel data models: pooled cross-sectional approach, random effects, fixed effect, between effects and within/between estimators. First, we assume the unobserved heterogeneity term to be zero and estimate the models as pooled cross-sectional ones, while adjusting for standard errors given the longitudinal dimension of the data. Although a useful starting point, the pooled model fails to check for unobserved time-invariant factors, such as entrepreneurial ability at the country level. For this reason, we apply both standard random- and fixed-effects panel estimators. In a similar vein, we adopt the between estimator suggested by Hauk and Wacziarg (2009), which has been shown to be more robust for measurement errors than other panel data estimators. Finally, we apply a hybrid approach (Schunck, 2013; Trevis Certo et al., 2017), which combines the advantages of both within and between estimators. The intuition behind this approach is that each explanatory variable is decomposed into within and between components and the model is run as a random-effects panel estimator. Using this approach allows us to disentangle the effect of OD on entrepreneurship in relation to: i) how it changes between countries (e.g., a group of countries characterised by higher levels of OD adoption are more entrepreneurial than countries belonging to a different group) and ii) within countries over time (e.g., a country can becomes more entrepreneurial by introducing or strengthening open data adoption).

Our dependent variable is the Global Entrepreneurship Index (*GEI*) developed by the Global Entrepreneurship and Development Institute (GEDI). *GEI* is an indicator ranging between 0 and 100 which is developed annually and measures the quality and the scale of the entrepreneurial process in more than 120 countries worldwide. It is a measure of entrepreneurial determinants at national level, based on three sub-indexes labelled as attitudes, abilities, and aspirations (Acs, Autio et al., 2014). Overall, these sub-indexes are composed of fourteen pillars.[2] Entrepreneurial

[2] https://thegedi.org/global-entrepreneurship-and-development-index/

attitudes refer to the identification of new opportunities, networking and risk acceptance. Entrepreneurial abilities are related to personal attributes, the capacity to adopt and implement technology and the development of strategies in order to be competitive in the market. Entrepreneurial aspirations refer to the innovation and quality of product development, attraction of risk capital and globalization. GEI index bears several advantages compared to other country-level indicators of entrepreneurship, such as the Global Entrepreneurship Monitor (GEM). First, GEI index is available for a high number of countries (137 countries compared to 50 countries for GEM). Second, GEI index has often been used in combination with institutional and survey data to analyse: contextual features of entrepreneurship (Ács et al. 2014); the association with economic growth (Acs, 2010); and the role that governments play in fostering entrepreneurship (Saberi and Hamdan, 2018). Moreover, contrary to other main measures of entrepreneurship at the country-level, GEI index is less biased towards low value-added activities and sectors (e.g. personal services) and provide a better account of digital industries. Finally, GEI index has been extensively used to provide policy and managerial recommendations (Szerb et al., 2013; Ács et al., 2014; Komlósi et al. 2015).

3.1.2 Explanatory variables

We measure the adoption of OD at the country-level by relying on the Open Data Barometer score, developed by the World Wide Web foundation.[3] The Open Data Barometer score comprises three types of data collection: i) a peer reviewed expert survey containing a range of questions about OD contexts, policy, implementation and impacts and a detailed assessment of 15 different data types for each country (data availability, format, license, timeliness and discoverability); ii) a government self-assessment through a simplified version of the survey above and iii) secondary data complementing primary data collection (for the readiness component only) with information

[3] https://opendatabarometer.org/

retrieved from official data of the World Economic Forum, World Bank, United Nations e-Government Survey and Freedom House. We preferred this source of data compared to others, such as the Global Open Data Index (Open Knowledge Foundation, 2019), as this is a multidimensional indicator composed of three main sub-indexes and ten pillars with a methodological approach to data collection that makes country data comparable through time, while other OD indicators have a narrow scope in terms of the publication of national government data and a methodology which has changed several times. The indicator comprises three main components: OD readiness, OD implementation, and OD impact. The component of readiness measures how qualified are government designing and adopting OD initiatives related to government actions, civil rights, business, and entrepreneurship. The implementation component measures not only the level of government data published but also the degree of accessibility, openness and timeliness. Finally, the impact indicator quantifies whether the data released by governments have a practical benefit to society in economic, social and political terms (Open Data Barometer, 2017). For our purpose, we rely on the implementation component of the Open Data Barometer score. We do so to avoid any problems of measurement error or spurious association between our open data measure and the entrepreneurship index as the readiness and impact components of the Open Data Barometer score are closely related to, for example, the impact of open data on the economy or its role for the creation of new businesses.

On the contrary, the implementation component of the open data index measures the extent to which government data is open, accessible and timely by scoring along these dimensions fifteen different types of datasets, thus reflecting a wide range of government functions. Our main indicator is a single score ranging between 0 and 100 for each country (*OD score*), where a higher level of the score implies a higher adoption of OD in the given country.

To measure institutional quality (*Inst Qual*) at the country level we follow a consolidated literature and rely on the World Bank's Worldwide Governance Indicators (WGI) (Kaufmann et al. 2010). These indicators monitor the process of government selections and transitions, the capacity to develop and implement reliable policies and the strength of institutions through the composition of six pillars: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption. We focus here on the control of corruption indicator, which captures "the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests" (pag 223, Kaufmann et al., 2011). We decided to focus on a single indicator proxying for institutional quality because all WGI indicators are highly correlated (Glaeser at al, 2004; Tebaldi and Elmslie, 2013), thus pointing to a high degree of overlapping of these measures (the correlation coefficients range between 0.7 and 0.9).[4] Furthermore, among the studies adopting WGI indicators to proxy for institutional quality, control of corruption is widely used (Perez-Villar and Seric, 2015; Aparicio et al., 2016; Chowdhury et al., 2019).

3.1.3 Control variables

We control for several factors which can affect the entrepreneurial level of a country. We proxy for the innovation activity of a country by relying on the number of patent applications as patents are considered by the literature as one important determinant of new firm formation (Somaya and Teece 2008; Choi and Phan 2006). *Innovation* is the number of patents filed under the Patent Cooperation Treaty (PCT) procedure per million people. *Access to the internet* is a measure of the total used capacity of international Internet bandwidth, in kylobytes per second (kb/s) divided by the number of users. We also consider the percentage of corporate taxation in a given country (*Corporate tax*) as an increase or reduction of it may encourage or inhibit the inclusion or exclusion on entrepreneurial activities (De Mooij and Nicodème 2006). *Labour market rigidity* is an index weighting legal and regulatory frameworks such as minimum wages, legality mandated notice

[4] Our results are broadly confirmed when we consider other WGI indicators.

period, obstacles to hiring additional workers or rigidity of hours on a given economy (Fuentelsaz et al. 2015). *Ease new business* and *ease credit* are two measures related to the regulatory environment that directly affect private entrepreneurial endeavours. The former quantifies the level of bureaucracy in terms of the number of procedures, time, cost and paid-in minimum capital requirement for a small- to medium-size limited liability company to start up and formally operate in a country. The latter measures two main financial components for a company in an economy: the access to finance and the effectiveness of collateral and bankruptcy laws in facilitating lending (World Bank Group 2019). Finally, we control for two standard measures which have been found to be related to the entrepreneurial level of a country (Russell et al., 2008): GDP per capita in 2010 PPP (*Income*) and the percentage of population enrolment in tertiary education (*Tertiary edu*). Table 1 provides a description of variables with name, data source and period of reference.

[Table 1 ABOUT HERE]

4 RESULTS

4.1 Descriptive results

Table 2 and Table 3 report the descriptive statistics and correlations for all the variables used in the analysis. As it is usual in analysis where the unit of observation is the country, in some cases correlation among variables is high. We have conducted an in-depth inspection of such correlations to examine whether multicollinearity represents a significant problem in our dataset. We implemented a full range of diagnostic methods found in the statistical literature. First, we calculated mean variance inflation factors. Variance inflation factors range between 1.29 and 4.87 with a mean variance inflation factor of 2.31, all well below the threshold value of 5 (Menard, 1995, Pag. 66). Second, condition index for the three specifications outlined above ranges between 1 and 20: all values below the threshold of 30 (Hair et al, 1998:220). Third, the Theil R2 multicollinearity effect equals 0.01 which is well below the value indicating multicollinearity, i.e. 1 (Theil, 1971).

[Table 2 ABOUT HERE]

[Table 3 ABOUT HERE]

Figure 1 shows a graphical representation of the two-way relationship between the level of OD adoption and the entrepreneurial score at the country-level. The upward sloping shape of the line points to a positive relation between the two measures: countries with a high level of OD are also countries characterised by a high level of entrepreneurship activity. Even more interestingly, the scatter diagram in Figure 2 illustrates the extent to which the relationship between OD adoption and entrepreneurship changes relative to the level of institutional quality (quartiles of the institutional quality distribution). Although the lines are upward sloping for all the four quartiles of institutional quality (low, medium-low, medium-high and high institutional quality), the lines gets steeper for high levels of institutional quality (particularly for the third and fourth quartiles) thus pointing to a greater role of OD for entrepreneurship in countries characterised by high institutional quality. The overall pattern from this first descriptive exercise shows a positive association between OD and entrepreneurship and an even greater role played by OD for countries characterised by high institutional quality.

Econometric results

We investigate how the extent of OD affects the level of entrepreneurship at the country-level building upon the different estimation models introduced in section 2.2. The main results are reported in Table 4. The first four columns present different panel data estimators (pooled, random effects, fixed effects and between effects respectively). Column 5 presents the results of the hybrid approach suggested by Schunck (2013), which combines the advantages of both within and between estimators and contributes the disentangle the two effects. As expected, both income per capita and the level of education affect the level of entrepreneurship at the country level: in fact both *Income* and *Tertiary edu* are positive and significant at standard confidence levels ($p<0.01$) in four specifications out of five.

Concerning OD, we observe a positive and significant association between OD and entrepreneurship using ordinary least squares, random effects and between effects estimators. As it was the case for the control variables, the effect is not significant for the fixed effect specification. The above result seems to suggest that the positive relation between OD and entrepreneurship is mainly due to differences in OD adoption between countries (i.e. a group of countries characterised by higher levels of OD adoption are more entrepreneurial than countries belonging to a different group) rather than within countries over time. This interpretation is confirmed by the results reported in column 5 where, via the hybrid approach, we find that it is indeed the between component of OD that shows a positive and significant association with entrepreneurship ($\beta = 0.824$, $p < 0.05$). Nevertheless, we find a positive ($\beta = 0.396$) and weak ($p < 0.1$) association between the within component of OD and entrepreneurship.

[Table 4 ABOUT HERE]

The picture emerging from the previous results appears more nuanced when we introduce interaction terms to capture the interplay between OD and country institutional quality in driving entrepreneurship. Table 5 reports our second specification, which adds to the former model the interaction between OD and institutional quality (*OD score X inst qual*). A positive sign would mean that the two constructs reciprocally reinforce; a negative sign would point to a substitution effect. Columns 1-5 of Table 5 report a positive and significant coefficient of *Open Data X Inst Qual* for all the different estimation strategies implemented. This result indicates a reciprocally reinforcing effect between OD and institutional quality for the level of entrepreneurship of a country. Interestingly, and contrary to the case of the direct effect, this effect is positive and significant ($p<0.05$) when country-level fixed effects are included (column 3 of Table 5) thus pointing to an effect that is both between and within countries (column 5 of Table 5). We provide a graphical representation of this result and plot the predicted values of the entrepreneurship score against *Open Data* for different values of *Institutional Quality* (respectively 10^{th}, 25^{th}, 50^{th}, 75^{th}

and 90th percentiles) in Figure 3. We do so relying on the fixed effect model (Column 3 of Table 5), but results are not different if other models are used. When all of the other variables are at their mean values, the marginal effect of Open Data is negative at very low levels of institutional quality (10th percentile); however, the marginal effects turn positive and are increasing for higher values of Institutional Quality (from the 25th percentile onward). Overall, this graph provides support for a complementarity between Open Data and Institutional Quality in relation to the entrepreneurial potential of a country.

[Table 5 ABOUT HERE]

5 ROBUSTNESS CHECKS

Endogeneity

A major concern with the estimated model is that there may be a potential endogeneity problem, i.e. there may be unobserved covariates simultaneously correlated with OD adoption and our measure of entrepreneurship that may be biasing our coefficients. For example, it might be the case that the demand for OD is higher in countries with a more digitally literate population. This would imply a higher ability to start ventures in the era of the digital economy.

We take into account these problems by instrumenting for our main independent variable (*OD score*) by resorting to an additional source of data: the World Values Survey which offers a wide range of country-specific cultural data and has been extensively used in cross-cultural and economics of education research.[5] We employ the longitudinal dataset comprising six different

[5] For a full list of publications please check http://www.worldvaluessurvey.org.

survey waves (1981-1984, 1989-1993, 1994-1998, 1999-2004, 2005-2009 and 2010-2014) and compute averages of our variables of interest for the overall period (1981-2014).[6] We exploit this data source and look at the presence of cultural factors which are likely to explain the higher adoption of OD at the country-level but not the level of entrepreneurship, thus providing a credible exclusion restriction for our estimation strategy. More precisely, we define *Open Mindedness* as a dummy variable taking value 1 if a respondent has indicated at least one of the following options: (i) imagination; (ii) tolerance and respect for other people while answering to the question "Here is a list of qualities that children can be encouraged to learn at home. Which, if any, do you consider to be especially important?". Similarly, we defined the variable *Voice* as one of the sub-indexes comprising the post-materialist index developed by Welzel (2013).[7] *Voice* measures the respondents' priorities for freedom of speech and for people having a voice and a say in how things are done in their society. To measure these priorities, three answers to a question asking which should be country priorities are used: (i) giving people more say in important government decisions; (ii) protecting freedom of speech; (iii) seeing that people have more say about how things are done at their jobs and in their communities. As information on these last variables is not available for all countries, the sample reduces to 203 observations (compared to the 273 originally available).

We adopt a standard two-stage least square IV estimator, although adopting two-step efficient generalized method of moments or limited–information maximum likelihood estimators (Hayashi, 2000; Baum et al., 2007) do not affect our results.[8] We are also careful to run a battery of appropriate statistical tests for our model. First, in the first stages we report various statistics that measure the relevance of the excluded exogenous variables (R^2, Adjusted R^2, Partial R^2 and robust F-statistic). Second, we check whether endogeneity is really an issue in our case by running an

[6] The dataset is freely available at http://www.worldvaluessurvey.org.

[7] For details on how the sub-index is constructed please refer to the online appendix of Welzel's book.

[8] Results are available from the authors upon request.

endogeneity test robust to heteroschedasticity (Wooldridge, 1995). Finally, we test the validity of the chosen instrumental variables via a Sargan-Hansen test of overidentifying restrictions.

Table 6 and Table 7 present the results for first-stages and final IV estimates respectively. We provide estimates for two just-identified models (columns 1 and 2 of Table 6; columns 1-4 of Table 7) and the over-identified one (column 3 of Table 6 and columns 5-6 of Table 7).

First of all, it must be noted that our main explanatory variables are affected by a problem of endogeneity. The endogeneity test rejects the null hypothesis of exogenous variables at standard significance levels (columns 1, 3 and 5 of Table 7). Quite reassuringly, the chosen instruments are correlated with the endogenous regressors to a good extent. This is apparent from the results of the first stage equations (Table 6). Both *Open Mindedness* and *Voice* are positively and significantly related to *Open data* both separately and together. Overall, the results from the instrumental variable regressions confirm the main results obtained in Table 4 and Table 5. Indeed, columns 1, 3 and 5 in Table 7 show positive and significant coefficients of the *OD score.* Similarly, columns 2, 4 and 6 confirm the positive moderating effect of institutional quality in the relationship between open data and entrepreneurship by showing positive and significant coefficients.

In an attempt to further control for the robustness of our results to a problem of weak instruments, we implement a Least Absolute Shrinkage and Selection Operator (LASSO) regression approach (Belloni et al., 2012). Notably, we use this approach to check whether our chosen instruments (*Open mindedness* and *Voice*) appear among a large number of IV candidates (Hain and Jurowetzki, 2019). We start with a large set of potential instruments (eleven) which include also our two instruments, all generated using questions from the World Values Survey.[9] We implement three different

[9] Our starting point was to select all variables from the world values survey database which have a high correlation with our OD score variable (above 0.5). After this, we are left with nine variables: 1) Disbelief Component of Secular Values; 2) Post-Materialist index (4-items); 3) Post-Materialist index (12-items); 4) Future changes: More emphasis

popular approaches to select the instruments: i) post-double selection approach (Belloni et al., 2014); ii) lasso-double orthogonalization and iii) post-lasso double orthogonalization (Chernozhukov et al., 2015). Results are reported in Table A1. Column 1 shows the results of the first stage regression. Reassuringly, both of our preferred instrumental variables (*Open mindedness* and *Voice*) are present in the final list following the LASSO selection procedure. More importantly, the results from the three different LASSO approaches yield comparable results for the effect of *OD score* on the entrepreneurship index at the country level (Columns 2, 3 and 4).

Other robustness checks

We conduct a further set of robustness checks pertaining to a number of issues which may affect our estimates.

A first set of robustness checks pertains to a possible measurement error in our key regressor (*Open Data score*). We test the robustness of our results to alternative definitions of OD. First, we use the Open Data barometer score comprising all the three components (OD readiness, OD implementation and OD impact) and not only OD implementation (as explained in Section 2.2.2). Second, we run our set of estimates using an alternative measure of OD: the Global Open Data Index (GODI). This indicator adopts a different methodology compared to the Open Data Barometer by evaluating the level of open data at the country level by scoring the datasets made available by governments and public institutions. Finally, we consider whether the overlap of OD and institutional quality induces a measurement error in our estimates. Among the others, the Open Data Barometer collects information about citizens and civil society by asking questions such as

on technology; 5) Defiance Component of Secular Values; 6) Equality Component of Emancipative Values; 7) Secular values index; 8) Open mindedness and 9) Voice. A detailed definition of items 1-7 in the list can be found in Welzel (2013, 2014), while items 8 and 9 are the two instrumental variables defined in Section 5.1.

“To what extent is there a robust legal or regulatory framework for protection of personal data in the country?” and about policies enacted by public administrations (“To what extent is there a well-defined OD policy and/or strategy in the country?”). Therefore, the OD score partially overlaps with our institutional quality measure, which captures different aspects of the quality of country-level governance. The overlap is considerate, as shown by the pairwise correlation between the two measures in our sample (around 0.8). We control for this potential issue of measurement error by regressing our measure of OD on *institutional quality* and predicting the residuals. These residuals represent the variance in the OD score that is not explained by the country's institutional quality. We then use these residuals as the new measure of OD (*Open data - residuals*). Table A2, Table A3 and Table A4 in the Appendix reports the main results for the three different definitions of OD. Reassuringly, the new measures of OD are still positive and significant and confirm results obtained in Table 4 and Table 5.

In the second set of robustness checks we control whether our estimates are driven by the choice of control of corruption from WGI indicators as the main proxy for institutional quality. First, we rerun our estimates by using all the other WGI indicators of institutional quality. As mentioned in Section 2.2.3, all of the WGI indicators are highly correlated (above 0.9) which means that they are likely to proxy for the same theoretical construct. This descriptive evidence is further corroborated by the results of our robustness check, which confirms our main results.[10] Second, instead of relying on a single indicator we take into consideration all of the six WGI indicators by taking the average as done in previous works (Knack and Keefer, 1995; Al-Marhubi, 2005; Bergh et al., 2014). Our results are corroborated by this further robustness check (see Table A5). Finally, we rely on a different data source: the Institutional Profile Database (IPD). IPD comprises 127 different

[10] We do not report the tables in the main manuscript as this would mean to add five more tables to an already excessively long appendix (one for each of the five remaining WGI indicators). Results are available from the authors upon request.

variables covering a wide range of country institutional and environmental aspects. We reduced the number of variables by performing a one factor principal components analysis on all variables within each of the four categories in IPD: A) political institutions B) markets for goods and services; C) capital market; D) labour market and social relations. This yields one principal component for each of the four sectors of IPD, which as single item accounts for the largest part of the variance within each category (between 40 and 45%). We then include the predicted scores one at the time (given the high correlation) in our estimates. Unfortunately, due to the availability of the data only for one year (2016), we are able to run only cross-sectional regressions. Interestingly, the only factor confirming our results is political institutions. Results for these further robustness checks are displayed in Table A6, Table A7, Table A8 and Table A9. [11]

6 DISCUSSION AND OUTLOOK

This paper has focused on OD, an asset that has been presented as the raw material for entrepreneurship in the digital age. Earlier examples have seen entrepreneurs develop innovative products and services using OD (Tinholt 2013; Magalhaes and Roseira 2017; Bonina 2013; Hughes-Cromwick and Coronado 2019). This has led policy-makers to view OD publication as a way of fuelling entrepreneurship in their digital economies (Huijboom and Van den Broek 2011; Cabinet Office 2012). This paper presents novel evidence to test this widely held assumption in a more systematic fashion. Based on a comparative and longitudinal analysis at country-level, a first contribution of the paper is to demonstrate an association between OD and entrepreneurship: there is a positive and significant relationship between the extent of adoption of OD and the entrepreneurial level of a country. The positive association between OD and entrepreneurship

[11] For ease of presentation the specifications without interaction effects are not reported. Results are similar to those reported in the text and are available from the authors upon request.

comes from differences across countries rather than from differences within countries through time, i.e. there are a group of countries which do particularly well in realising the entrepreneurial benefits of OD.

However, our results highlight that mere publishing of OD is not sufficient for entrepreneurial outcomes. A second contribution of this paper is to highlight the important role of country-level institutions for enabling entrepreneurial activity (Acs et al., 2008; Audretsch et al. 2007). The results of our study show that within the context of OD, publishing OD is not sufficient for its entrepreneurial exploitation. We show that the quality of country-level institutions, understood as the 'rules of the game' regarding the implementation of rules supporting contractual relationships and market exchanges, positively moderate the relationship between published OD and country-level entrepreneurship. The relationship between OD adoption and entrepreneurship is particularly strong in countries with high institutional quality. This stems from an effect which is both across countries and within countries through time. Overall, our results show that unless a country has quality institutions, publishing OD does not positively affect entrepreneurship.

To our knowledge, our work is the first to provide large scale evidence on the positive role of OD at the country-level. For this reason, it is probably too early to draw detailed implications from our results. Nevertheless, we trust that a number of general and specific provisions can be set forward which can inform the current debate on the value and governance of data (Savona, 2019).

The entrepreneurial tech sector is not expected to automatically exploit the data provided, but benefiting from initiatives such as OD require a wider appreciation of traditional governance dimensions, specifically those regarding the implementation of rules supporting contractual relationships and market exchanges. The results support the importance of broader policy initiatives to develop good governance (Gupta and Abed, 2002).

Furthermore, the results of our study strongly support the argument that OD is beneficial to entrepreneurship, and given that most OD is currently published by public sector organisations, public policy could facilitate more publishing of OD by private sector organisations. Assuring protection of privacy, policy makers could enforce antitrust measures in the management of personal data to put individuals in control of whether they want to share data for the public good (see e.g. DECODE, 2019; Savona, 2019).

Whilst our results show robust results with a range of robustness checks, there are the usual limitations regarding the underlying causal mechanisms, particularly related to the lack of an experimental setting. The relationship we find can be eminently correlation due to a number of causes: the short time-frame of the analysis, composite measures of relevant indices, partial residual correlation of instrumental variables to our dependent variable. For all of the above reasons, attaching a casual meaning to our results should be approached with caution. Moreover, caution is be needed also on the cross-country comparisons, that in some case might not be very revealing due to the many incomparable institutional differences. In particular, since empirical indicators of institutional quality regarding broad property rights and corruption are highly correlated, it is difficult to disentangle the exact role of specific sub-components of institutions (Woodruff, 2006). There is a need to examine how sub-types of institutional quality affect specific entrepreneurial outcomes by empirically examining country-level characteristics in more detail with different (ideally experimental) methodological approaches. Finally, we acknowledge the noisy nature of our dependent variable (the global entrepreneurship index), which is likely to measure both low (e.g. hairdressers, kebab shops) and high value-added activities (with the last ones more directly related to open government data).

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Figure 1: Relationship between open data and entrepreneurship

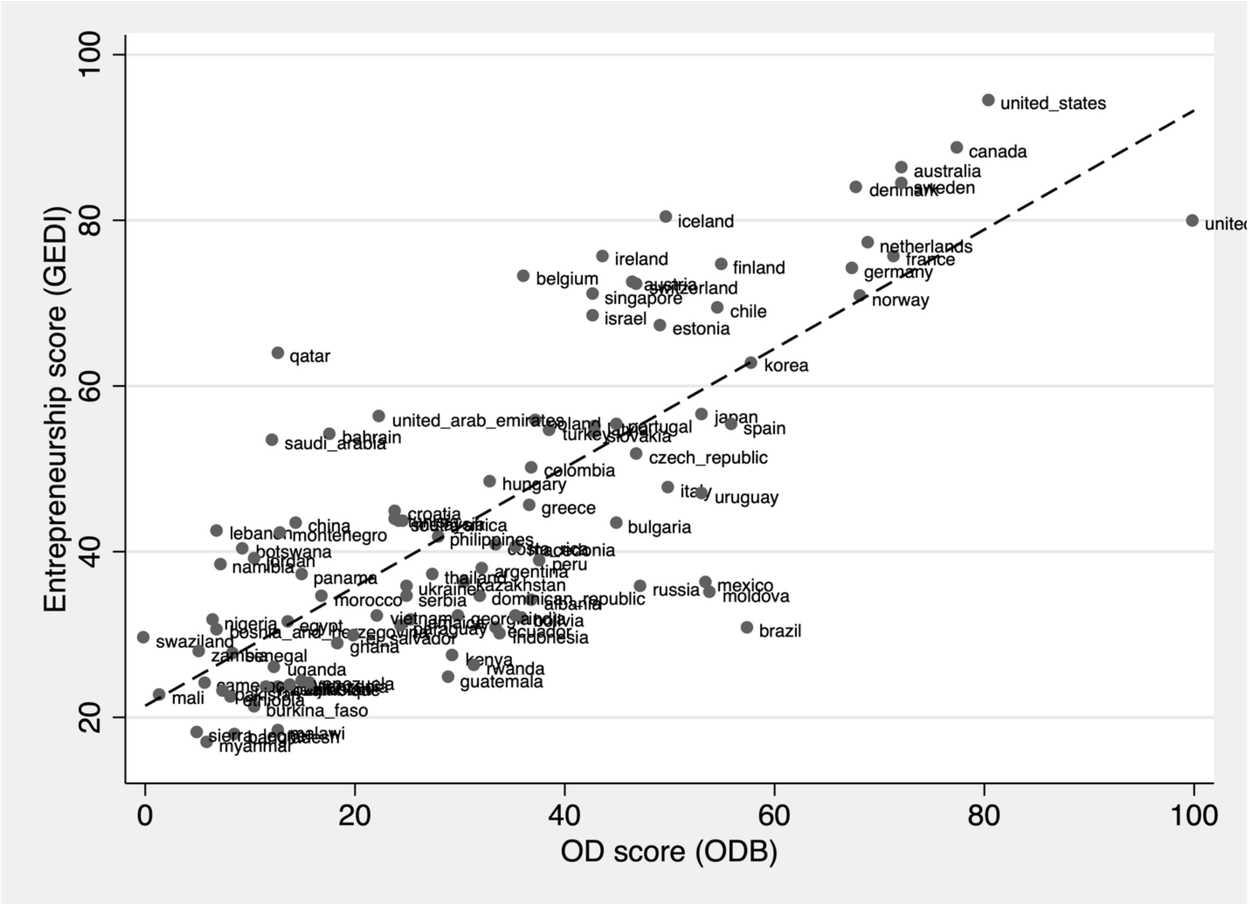

Figure 2: Moderating effect of institutional quality on the relationship between open data and entrepreneurship

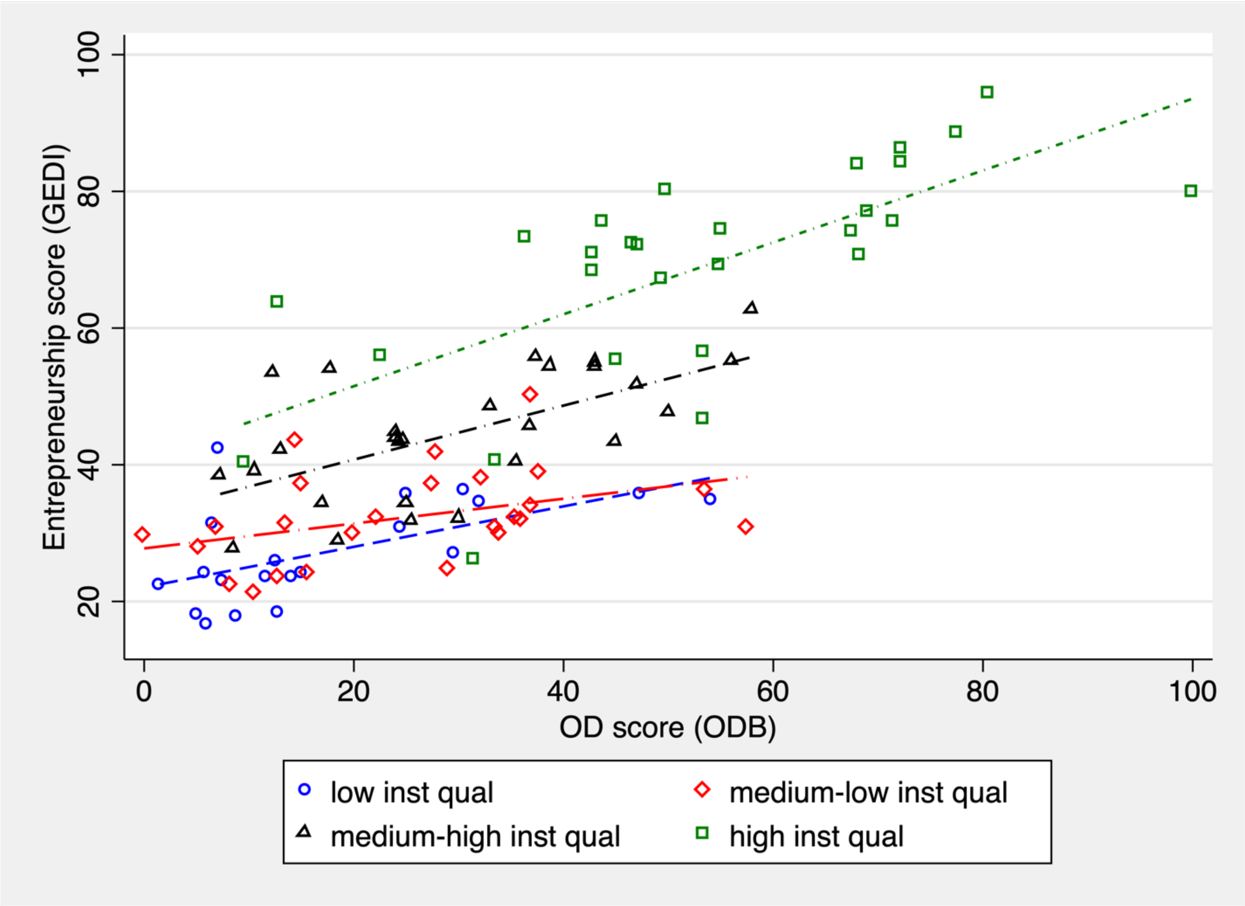

Figure 3: The effect of open data on entrepreneurship for different percentiles of institutional quality

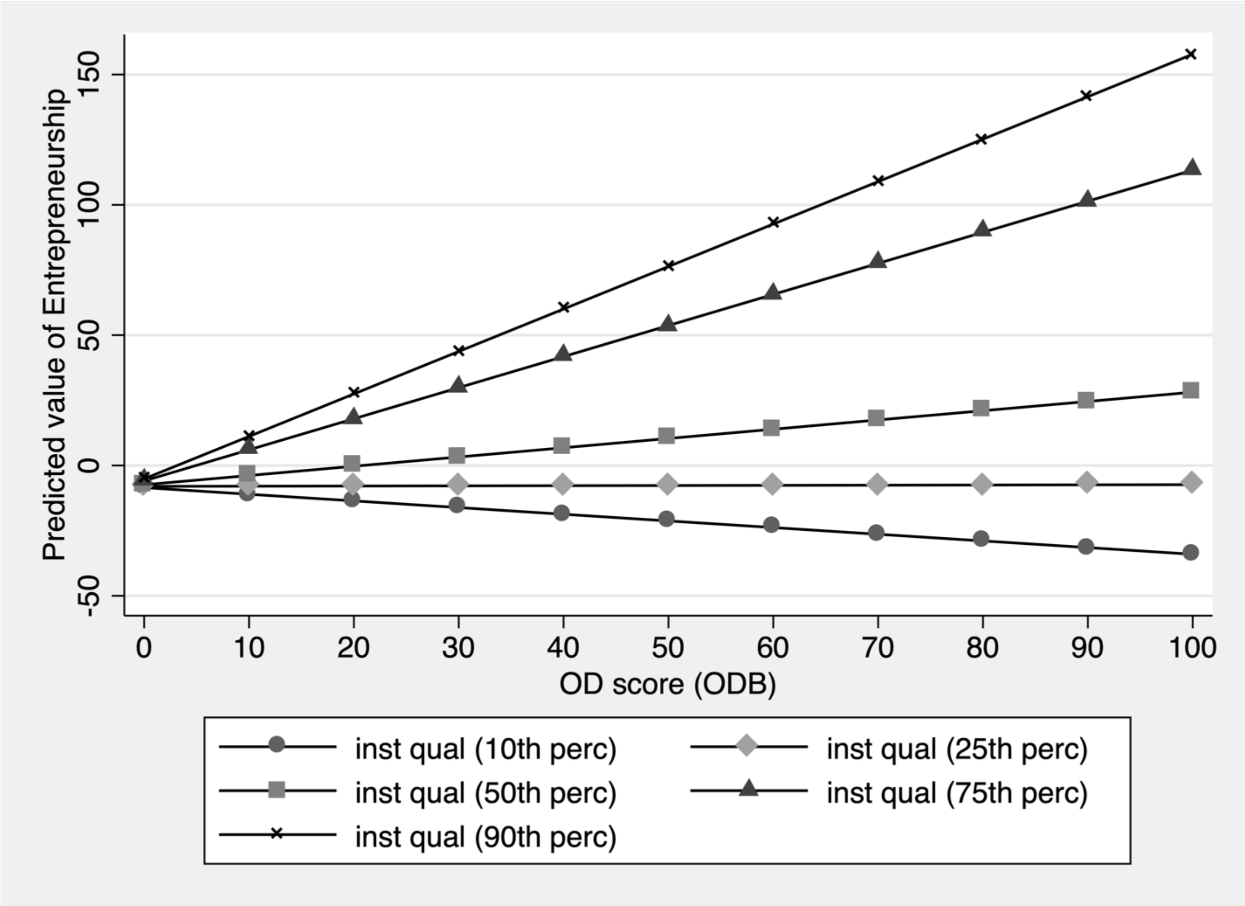

Table 1: Description of variables

Name	Source	Description	Period
Dependent Variable:			
GEI	The Global Entrepreneurship and Development Institute (GEDI)	Global Entrepreneurship Index (GEI)	2013-2016
Independent Variables			
Open Data (OD) score	The Open Data Barometer (ODB)	Open Data implementation component of the Open Data Barometer score	2013-2016
Inst Qual	The Worldwide Governance Indicators (WGI)	Control of corruption	2013-2016
Control variables			2013-2016
Innovation	The Global Competitiveness Report (GCR)	Number of patents filed under the patent cooperation treaty (PCT) per million people	2013-2016
Access to the internet	The Global Competitiveness Report (GCR)	*I*nternet bandwidth measured as number of kilobyte per second divided by the number of users	2013-2016
Corporate tax	Economic Freedom Index (EFI)	Corporate tax rate	2013-2016
Income	Economic Freedom Index (EFI)	GDP per capita in 2010 PPP	2013-2016
Labour market rigidity	Economic Freedom Index (EFI)	Labour freedom component of the economic freedom index which takes into account legal and regulatory aspects of a country's labour market (e.g. minimum wage, laws inhibiting layoffs, etc.)	2013-2016
Tertiary edu	Economic Freedom Index (EFI)	Percentage of population enrolled in tertiary education	2013-2016
Ease new business	Economic Freedom Index (EFI)	Ease of starting a business	2013-2016
Ease credit	Economic Freedom Index (EFI)	Ease of getting credit	2013-2016

Table 2: Descriptive statistics

variable	mean	p50	sd	min	max	N
GEI	41.06	37.70	18.44	0	86.2	273
OD score	35.44	35	22.73	0	100	273
Inst Qual	50.21	42.22	25.90	8.51	100	273
Innovation	50.09	3.28	86.59	0	335.38	273
Corporate Tax	24.44	25.00	8.52	0	45	273
Income	22397.09	16723.00	20196.51	780	143427	273
Access to the internet	89.66	46.68	121.89	0.23	737.01	273
Tertiary edu	46.45	47.59	27.72	0.80	116.62	273
Labour market rigidity	63.24	62.50	14.79	26.3	98.5	273
Ease credit	60.29	60.00	18.98	0	100	273
Ease new business	84.08	86.20	9.66	55.2	99.1	273

Table 3: Correlation table

		1	2	3	4	5	6	7	8	9	10
1	GEI	1									
2	OD score	0.73	1.00								
3	Inst Qual	0.80	0.69	1.00							
4	Innovation	0.65	0.58	0.74	1.00						
5	Corporate Tax	-0.28	-0.04	-0.25	-0.04	1.00					
6	Income	0.73	0.49	0.73	0.55	-0.48	1.00				
7	Access to the internet	0.64	0.54	0.69	0.60	-0.17	0.58	1.00			
8	Tertiary edu	0.72	0.68	0.62	0.51	-0.23	0.52	0.54	1.00		
9	Labour market rigidity	0.26	0.13	0.29	0.18	-0.26	0.28	0.19	0.09	1.00	
10	Ease credit	0.36	0.45	0.35	0.25	-0.06	0.18	0.25	0.33	0.32	1.00
11	Ease new business	0.55	0.49	0.57	0.37	-0.22	0.44	0.45	0.54	0.16	0.42

Table 4 The relationship between open data and entrepreneurship

	(1) POOLED	(2) RE	(3) FE	(4) BE	(5) WI_BW
OD score	0.881***	0.719***	0.343	0.716*	
	[0.196]	[0.223]	[0.224]	[0.372]	
OD btw effect					0.824**
					[0.325]
OD within effect					0.396*
					[0.233]
Inst Qual	1.097***	1.060***	0.755	1.045***	1.136***
	[0.213]	[0.308]	[1.169]	[0.382]	[0.331]
Innovation	0.055	0.079	2.451	0.054	0.044
	[0.065]	[0.086]	[1.677]	[0.105]	[0.093]
Corporate Tax	-0.178	-0.011	-2.381	0.120	0.086
	[0.467]	[0.647]	[1.915]	[0.752]	[0.642]
Income	0.001***	0.001***	0.001	0.001**	0.001***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]
Access to the internet	0.014	0.020	-0.030	0.001	0.003
	[0.035]	[0.053]	[0.088]	[0.072]	[0.056]
Tertiary edu	0.857***	0.944***	0.494	1.019***	0.928***
	[0.156]	[0.234]	[1.029]	[0.318]	[0.253]
Labour market rigidity	0.299	0.239	-1.058	0.322	0.343
	[0.218]	[0.301]	[0.945]	[0.346]	[0.285]
Ease credit	0.092	-0.062	-0.754**	0.294	0.270
	[0.153]	[0.199]	[0.345]	[0.275]	[0.235]
Ease new business	0.284	0.280	-0.478	0.222	0.182
	[0.397]	[0.405]	[0.639]	[0.520]	[0.505]
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R sq	0.805		0.210	0.878	
Country-year obs	273.000	273.000	273.000	273.000	273.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Table 5: The interplay between open data and institutional quality for entrepreneurship

	(1) OLS	(2) RE	(3) FE	(4) BE	(5) WI_BW
OD score	-0.697**	-0.783**	-0.725	-1.138**	
	[0.328]	[0.370]	[0.541]	[0.542]	
OD btw effect					-0.862*
					[0.471]
OD within effect					-1.144
					[0.785]
OD score X inst qual	0.027***	0.027***	0.019**	0.033***	
	[0.006]	[0.007]	[0.008]	[0.009]	
OD btw effect X inst qual					0.029***
					[0.008]
OD within effect X inst qual					0.028**
					[0.013]
Inst qual	0.085	0.048	-0.028	-0.218	0.050
	[0.319]	[0.373]	[1.073]	[0.524]	[0.446]
Innovation	-0.002	0.008	2.403	-0.027	-0.024
	[0.068]	[0.081]	[1.655]	[0.094]	[0.086]
Corporate Tax	-0.301	-0.133	-2.177	-0.067	-0.071
	[0.442]	[0.603]	[1.954]	[0.674]	[0.619]
Income	0.001***	0.002***	0.001	0.002***	0.002***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]
Access to the internet	-0.008	-0.001	-0.030	-0.029	-0.026
	[0.034]	[0.050]	[0.089]	[0.066]	[0.052]
Tertiary edu	1.030***	1.087***	0.504	1.207***	1.098***
	[0.161]	[0.223]	[1.041]	[0.299]	[0.248]
Labour market rigidity	0.327	0.321	-0.907	0.332	0.364
	[0.207]	[0.262]	[0.888]	[0.295]	[0.265]
Ease credit	0.176	0.032	-0.725**	0.435*	0.384*
	[0.145]	[0.186]	[0.343]	[0.258]	[0.227]
Ease new business	0.234	0.232	-0.401	0.139	0.066
	[0.375]	[0.371]	[0.660]	[0.535]	[0.470]
Year FEs	yes	yes	yes	yes	yes
R sq	0.820		0.220	0.899	
Country-year obs	273.000	273.000	273.000	273.000	273.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Instrumental variable regressions: first stages

	(1) OD score	(2) OD score	(3) OD score
IV open mindedness	0.286***		0.138**
	[0.068]		[0.066]
IV voice		0.314***	0.266***
		[0.067]	[0.070]
inst qual	0.253**	0.314***	0.257**
	[0.114]	[0.098]	[0.104]
patents/mil pop	0.002	-0.001	-0.001
	[0.015]	[0.014]	[0.014]
corporate tax rate(%)	0.299**	0.303**	0.241*
	[0.135]	[0.118]	[0.124]
GDP per capita (ppp)	0.000*	0.000	0.000
	[0.000]	[0.000]	[0.000]
Internet bandwidth (kb/s per user)	-0.025***	-0.028***	-0.026***
	[0.008]	[0.008]	[0.007]
tertiary edu enrollment (%)	0.231***	0.221***	0.209***
	[0.051]	[0.051]	[0.051]
labour freedom	-0.035	-0.045	-0.021
	[0.055]	[0.059]	[0.059]
ease of credit	0.293***	0.225***	0.229***
	[0.052]	[0.051]	[0.051]
ease of starting a business	-0.162	-0.103	-0.119
	[0.172]	[0.174]	[0.171]
Year FEs	yes	yes	yes
First Stage R sq	0.681	0.703	0.707
First Stage Adjusted R sq	0.659	0.682	0.685
First Stage Partial R sq	0.068	0.132	0.145
First Stage Robust F	17.542***	21.853***	13.835***
R sq	0.681	0.703	0.707
Obs	203.000	203.000	203.000

Dependent variable is the implementation component of the Open Data Barometer score (OD score) which is a single score ranging between 0 and 100 for each country. Robust standard errors are in parentheses. IV voice has missing values for 70 country-year observations, thus reducing the number of observations to 203 compared to other estimates.

Table 7: Instrumental variable regressions: the relationship between open data and entrepreneurship

	(1)	(2)	(3)	(4)	(5)	(6)
OD score	3.222**	0.409	2.282**	0.450	2.497***	0.419
	[1.317]	[1.211]	[0.957]	[1.804]	[0.916]	[1.043]
inst qual	0.197	-0.950	0.570	-1.347*	0.484	-1.122
	[0.786]	[0.778]	[0.586]	[0.694]	[0.603]	[0.694]
OD score X inst qual		0.033**		0.039***		0.036***
		[0.014]		[0.014]		[0.011]
patents/mil pop	-0.075	-0.105*	-0.070	-0.113*	-0.071	-0.109*
	[0.076]	[0.061]	[0.074]	[0.064]	[0.074]	[0.062]
corporate tax rate(%)	-1.380	-1.208*	-0.924	-1.429*	-1.029	-1.302**
	[0.866]	[0.647]	[0.716]	[0.777]	[0.706]	[0.629]
GDP per capita (ppp)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Internet bandwidth (kb/s per	0.051	0.029	0.023	0.041	0.030	0.034
	[0.074]	[0.066]	[0.070]	[0.069]	[0.070]	[0.064]
tertiary edu enrollment (%)	0.176	0.558*	0.434	0.481	0.375	0.526*
	[0.424]	[0.330]	[0.352]	[0.420]	[0.342]	[0.308]
labour freedom	0.556	0.493*	0.458	0.536	0.480	0.511*
	[0.352]	[0.286]	[0.302]	[0.332]	[0.309]	[0.290]
ease of credit	-0.610	-0.145	-0.315	-0.228	-0.382	-0.179
	[0.411]	[0.372]	[0.382]	[0.445]	[0.353]	[0.333]
ease of starting a business	1.101	0.808	0.969	0.831	0.999	0.817
	[0.848]	[0.616]	[0.703]	[0.715]	[0.732]	[0.634]
Year FEs	yes	yes	yes	yes	yes	yes
R sq	0.662	0.767	0.720	0.756	0.709	0.763
Obs	203.000	203.000	203.000	203.000	203.000	203.000
Endogeneity test	3.449*	1.035	3.207*	0.538	4.814**	1.673
Hansen J test					0.574[1]	1.566[2]

Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. The endogeneity test is robust to heteroschedasticity (Hayashi, 2000). The Sargan-Hansen test of overidentifying restrictions is reported. Robust standard errors and degrees of freedom are in parentheses. *IV voice* has missing values for 70 country-year observations, thus reducing the number of observations to 203 compared to other estimates.

APPENDIX

Table A 1: The relationship between open data and entrepreneurship – LASSO IV

	(1) First- stage	(2) Post-double selection	(3) Lasso- Double orthogonalizati	(4) Post-lasso Double
OD score		1.237** [0.568]	1.261*** [0.45]	1.162** [0.59]
inst qual	0.209*** [0.072]			
patents/mil pop	-0.025 [0.015]			
corporate tax rate(%)	0.325*** [0.118]			
GDP per capita (ppp)	0.000* [0.000]			
tertiary edu enrollment (%)	0.189*** [0.055]			
ease of credit	0.125*** [0.045]			
IV Open mindedness	0.097* [0.056]			
IV Voice	0.169** [0.067]			
IV Equality	0.144** [0.062]			
IV Disbelief	0.131** [0.055]			
Year FEs	yes			
Observations	198	198	198	198

Robust standard errors are in parentheses. Model is a Least Absolute Shrinkage and Selection Operator (LASSO) regression approach (Belloni et al., 2012). We start with a large set of potential instruments (eleven) which include also our two instruments, all generated using questions from the World Values Survey: 1) Disbelief Component of Secular Values; 2) Post-Materialist index (4-items); 3) Post-Materialist index (12-items); 4) Future changes: More emphasis on technology; 5) Defiance Component of Secular Values; 6) Equality Component of Emancipative Values; 7) Secular values index; 8) Open mindedness and 9) Voice. A detailed definition of items 1-7 in the list can be found in Welzel (2013, 2014), while items 8 and 9 are the two instrumental variables defined in Section 5.1. We implement three different popular approaches to select the instruments: i) in column 2 the post-double selection approach (Belloni et al., 2014); ii) in column 3 the lasso-double orthogonalization and iii) in column 4 the post-lasso double orthogonalization (Chernozhukov et al., 2015). Some of the instrumental variables above have missing values for 75 country-year observations, thus reducing the number of observations to 198 compared to other estimates.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Robustness check – the OD Barometer full indicator

	(1) POOLED	(2) RE	(3) FE	(4) BE	(5) WI_BW
OD score	1.042***	0.824***	0.057	0.888**	
	[0.283]	[0.295]	[0.465]	[0.392]	
OD btw effect					1.018***
					[0.328]
OD within effect					0.243
					[0.565]
Inst Qual	1.090***	1.061***	0.779	1.043***	1.126***
	[0.323]	[0.314]	[1.152]	[0.395]	[0.334]
R sq	0.809		0.205	0.881	
Country-year obs	273.000	273.000	273.000	273.000	273.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) POOLED	(2) RE	(3) FE	(4) BW	(5) WI_BW
OD score	-0.436	-0.717	-1.357	-0.784	
	[0.409]	[0.438]	[1.189]	[0.613]	
OD btw effect					-0.434
					[0.509]
OD within effect					-2.198
					[1.576]
OD score X inst qual	0.025***	0.028***	0.027*	0.030***	
	[0.008]	[0.008]	[0.016]	[0.010]	
OD btw effect X inst qual					0.025***
					[0.008]
OD within effect X inst qual					0.045*
					[0.025]
inst qual	0.159	0.049	-0.046	-0.037	0.212
	[0.409]	[0.392]	[1.026]	[0.520]	[0.445]
R sq	0.821		0.218	0.897	
Country-year obs	273.000	273.000	273.000	273.000	273.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: The relationship between open data and entrepreneurship – the open data GODI score

	(1) POOLED	(2) RE	(3) FE	(4) BE	(5) WI_BW
OD score	0.144***	0.113**	0.064	0.175**	
	[0.031]	[0.048]	[0.051]	[0.070]	
OD btw effect					0.176***
					[0.058]
OD within effect					0.061
					[0.060]
inst qual	1.341***	1.223***	0.706	1.125***	1.241***
	[0.222]	[0.330]	[1.303]	[0.355]	[0.332]
Controls	yes	yes	yes	yes	yes
R sq	0.769		0.233	0.875	
Country-year obs	310.000	310.000	310.000	310.000	310.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) POOLED	(2) RE	(3) FE	(4) BE	(5) WI_BW
OD score	-0.092	-0.100	-0.015	-0.148	
	[0.061]	[0.095]	[0.141]	[0.135]	
OD btw effect					-0.125
					[0.105]
OD within effect					-0.026
					[0.176]
OD score X inst qual	0.005***	0.004*	0.002	0.006***	
	[0.001]	[0.003]	[0.004]	[0.002]	
OD btw effect X inst qual					0.006***
					[0.002]
OD within effect X inst qual					0.002
					[0.004]
inst qual	1.278***	1.186***	0.774	1.140***	1.186***
	[0.217]	[0.313]	[1.299]	[0.341]	[0.305]
Controls	yes	yes	yes	yes	yes
R sq	0.780		0.236	0.888	
Country-year obs	310.000	310.000	310.000	310.000	310.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: The relationship between open data and entrepreneurship –OD cleansed of institutional quality

	(1) OLS	(2) RE	(3) FE	(4) BE	(5) WI_BW
OD score	0.881***	0.719***	0.343	0.716*	
	[0.196]	[0.223]	[0.224]	[0.367]	
OD btw effect					0.836***
					[0.324]
OD within effect					0.399
					[0.250]
inst qual	1.626***	1.492***	0.961	1.476***	1.640***
	[0.246]	[0.359]	[1.135]	[0.464]	[0.380]
R sq	0.805		0.210	0.878	
Country-year obs	273.000	273.000	273.000	273.000	273.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) POOLED	(2) RE	(3) FE	(4) BE	(5) WI_BW
OD score	-1.092***	-1.117***	-0.695	-1.604**	
	[0.414]	[0.427]	[0.629]	[0.677]	
OD btw effect					-1.311**
					[0.566]
OD within effect					-1.103
					[0.867]
OD score X inst qual	0.035***	0.034***	0.019*	0.044***	
	[0.008]	[0.008]	[0.010]	[0.014]	
OD btw effect X inst qual					0.039***
					[0.012]
OD within effect X inst qual					0.028**
					[0.014]
inst qual	1.270***	1.220***	0.838	1.046***	1.266***
	[0.238]	[0.324]	[1.081]	[0.402]	[0.351]
Controls	yes	yes	yes	yes	yes
R sq	0.822		0.219	0.901	
Country-year obs	273.000	273.000	273.000	273.000	273.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 5: Robustness check – Average value of WGI institutional quality indicators

	(1) POOLED	(2) RE	(3) FE	(4) BE	(5) WI_BW
OD score	0.717***	0.601***	0.376*	0.562	
	[0.256]	[0.215]	[0.221]	[0.358]	
OD btw effect					0.652**
					[0.325]
OD within effect					0.396*
					[0.234]
inst qual	1.935***	1.941***	2.570	1.720***	1.888***
	[0.386]	[0.402]	[2.421]	[0.531]	[0.411]
Controls	yes	yes	yes	yes	yes
R sq	0.813		0.216	0.883	
Country-year obs	273.000	273.000	273.000	273.000	273.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) POOLED	(2) RE	(3) FE	(4) BW	(5) WI_BW
OD score	-1.465***	-1.524***	-1.173	-2.061***	
	[0.520]	[0.495]	[0.759]	[0.663]	
OD btw effect					-1.746***
					[0.562]
OD within effect					-1.831*
					[0.994]
OD score X inst qual	0.033***	0.034***	0.025**	0.041***	
	[0.009]	[0.008]	[0.011]	[0.010]	
OD btw effect X inst qual					0.037***
					[0.009]
OD within effect X inst qual					0.037**
					[0.015]
inst qual	0.750	0.727*	1.468	0.300	0.643
	[0.457]	[0.427]	[2.526]	[0.584]	[0.508]
Controls	yes	yes	yes	yes	yes
R sq	0.829		0.227	0.907	
Country-year obs	273.000	273.000	273.000	273.000	273.000

Robust standard errors clustered by country are in parentheses. Models are pooled (column 1), random effects panel data (column 2), fixed effects panel data (column 3), between estimator as in Hauk and Wacziarg (2009) (column 4) and hybrid approach as in Schunck (2013) (column 5). R squared is reported for relevant specifications only (pooled, fixed effects and between estimator). Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 6: The interplay between open data and institutional quality for entrepreneurship – quality of political institutions from IPD

	(1)	(2)
OD score	0.972**	0.554
	[0.386]	[0.378]
OD score X inst		0.718**
		[0.226]
inst qual	29.214*	4.073
	[13.659]	[16.285]
Controls	Yes	yes
R sq	0.867	0.879
Country-year obs	141.000	141.000

Robust standard errors clustered by country are in parentheses. Models are both pooled Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 7: The interplay between open data and institutional quality for entrepreneurship – quality of institutions in the markets for goods and services from IPD

	(1)	(2)
OD score	0.126	0.043
	[0.393]	[0.390]
OD score X inst		0.204
		[0.313]
inst qual	-2.443	-10.133
	[12.529	[17.122
Controls	Yes	yes
R sq	0.684	0.686
Country-year obs	92.000	92.000

Robust standard errors clustered by country are in parentheses. Models are both pooled Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 8: The interplay between open data and institutional quality for entrepreneurship – quality of institutions in the market for capital from IPD

	(1)	(2)
OD score	0.826**	0.728
	[0.324]	[0.449]
OD score X inst qual		0.103
		[0.217]
inst qual	11.652	7.937
	[7.583]	[11.121]
Controls	Yes	yes
R sq	0.819	0.819
Country-year obs	134.000	134.000

Robust standard errors clustered by country are in parentheses. Models are both pooled Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 9: The interplay between open data and institutional quality for entrepreneurship – quality of institutions in the labour market from IPD

	(1)	(2)
OD score	0.774**	0.622
	[0.291]	[0.380]
OD score X inst		0.217
		[0.231]
inst qual	-7.047	-17.283
	[10.346]	[10.402
Controls	Yes	yes
R sq	0.899	0.900
Country-year obs	194.000	194.00

Robust standard errors clustered by country are in parentheses. Models are both pooled Dependent variable is the Global Entrepreneurship Index (GEI) which measures the entrepreneurial potential of a country on a scale from 0 to 100. Base sample in all columns is an unbalanced panel for 2013–2016. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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