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Tax Haven Welfare and the Crackdown on Secrecy: Evidence from Night Light Emissions

Abstract

Following numerous high-profile international initiatives, tax haven jurisdictions have been nudged into agreeing on tax information exchange. We analyse whether these agreements had measurable effects on the economy of cooperative tax havens. As GDP data are missing for many small tax haven jurisdictions, we use night light data as a proxy for economic activity. Depending on the exact list of tax havens, using this proxy allows us to increase the number of tax haven jurisdictions by up to 25 percent compared to using GDP. We find that tax havens which have signed more tax information exchange agreements experienced a significantly higher economic activity, as proxied by the sum of night light emissions. This applies to agreements that provide information exchange on request as well as agreements that implement automatic information exchange. When we use GDP as a measure of economic activity, tax information exchange agreements are not associated with a differential development of economic activity. Both observations suggest that information exchange treaties so far have not reduced economic growth in more cooperative tax havens.

JEL-Codes: H260, H870, O110.

Keywords: tax haven, night light emissions, tax information exchange, economic development.

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1. Introduction

Tax haven countries and offshore financial centres act as hubs for an increasing share of international capital (Alstadsaeter et al., 2018; Milesi-Ferretti and Lane, 2017; Zucman, 2013; Damgaard et al., 2019; Miethe, 2020). These tax havens are often considered as instruments to conduct profit shifting, tax evasion, and illicit financial flows (Miethe, 2020).

Several policy inititatives try to reduce the role of tax havens in facilitating these activities. A prominent example is the high-profile OECD initiative to combat harmful tax evasion which aims at discouraging OECD member countries as well as some non-OECD tax havens from pursuing policies that are argued to unfairly erode other countries' tax bases and thus harm other countries (OECD, 1998; OECD, 2000; OECD, 2004). Following up on this initiative, OECD member countries have implemented numerous bilateral tax information exchange agreements (TIEAs) and double tax conventions (DTCs), allowing for tax information exchange on request (IoR) between tax authorities. These agreements stipulate that a local country must provide tax related information to a requesting partner country, even if the information usually is not required by the local country and may therefore imply extra effort. Consequently, these agreements puncture bank secrecy with the aim of reducing cross-border tax evasion. More recently, automatic exchange of information (AEOI) has been introduced by the OECD Mutual Competent Authority Agreement under its Common Reporting Standard (CRS).

Previous literature, as summarized below, mainly has examined tax information agreements from the point of view of high-tax countries. Among other things, the literature has addressed the effect of tax information exchange treaties on cross-border non-bank deposits in tax haven jurisdictions. The empirically negative effect has been taken as evidence for the (partial) success of these agreements (Casi et al., 2019).

To the extent tax haven jurisdictions have benefitted from the absence of transparency, the success of information exchange agreements may come at an economic cost to them. Eclectic evidence exists on the structure of benefits from being a tax haven and different tax havens may derive different types of benefits. de Mooij et al. (2020) report that corporate special purpose entities, which may be attracted to Luxembourg for non-tax as well as for tax reasons and which primarily act as conduit entities, account for some three percent of the country's business tax revenue. In the British Virgin Islands, an important conduit country for investments into China, fees from the international business and finance centre accounted for 68 percent of total tax revenues in 2016 (Capital Economics, 2017, p. 13).[4] For a jurisdiction with a workforce of some 20,000, the relatively modest amount of US$ 225m can make a considerable difference. In addition, the jobs in the international business and finance center offer above average wages, although the design of financial products often relies on expertise from the financial industry in Asia, particularly in Hong Kong (Robertson, 2019, pp. 18-19).

Currently, we lack information on the extent to which these international activities on combating tax evasion translate into measurable effects on the economic conditions in cooperative tax havens. One difficulty in addressing this issue is data availability. For a considerable number of tax haven jurisdictions, yearly GDP data is missing. Therefore, the present paper addresses the impact of tax information exchange treaties on the economic conditions in tax havens by using night lights data collected by the NASA as a proxy for GDP. We use the NOAA harmonized DMSP-VIIRS yearly night light dataset (see Li et al., 2020), which spans from 1992 to 2018 and covers all tax havens. Our main dataset is a balanced sample of 1,917 observations from 71 tax havens. Night light data allows increasing observations by up to 25% compared to using standard GDP measures. Numerous jurisdictions, such as Guernsey, Jersey or the British Virgin Islands, may be included that otherwise would have to be dropped.

Using night light emissions to proxy economic activity, our results indicate that the conclusion of tax information exchange treaties is followed by increased rather than depressed economic activity. This may come as a surprise as tax havens usually are deemed to benefit from tax secrecy and needed to be arm-twisted into more transparencies by the set-up of black and grey lists. If we use GDP data instead of night light data, the signing of exchange information treaties turns insignificant. In both cases, our findings suggest that information exchange agreements did not translate into lower economic growth in tax havens. This applies to agreements that provide for information exchange on request as well as those agreements that govern automatic information exchange.

Our research relates to and expands several strands of the literature. One strand has studied the effect of policy measures on cross-border bank deposits (Johannesen, 2014; Johannesen and Zucman, 2014; Langenmayr, 2017; Menkhoff and Miethe, 2019; Miethe, 2020). There are also papers that look at the effects of policy measures on the outbound investments coming from tax haven jurisdictions (Hanlon et al., 2015; Heckemeyer and Hemmerich, 2020; Miethe, 2020).

[4] Konrad and Stolper (2016) provide an explanation for why competition between tax havens may not be able to compete to zero those fees when tax haven reputation is important.

The allocation of (hidden) wealth is considered in Andersen et al. (2017, 2020) and Miethe (2020).

Our research also relates to the literature on profit shifting by multinational enterprises (MNEs). Firms often use subsidiaries in tax haven countries in order to avoid taxation. For an overview, see Beer et al. (2020), Riedel (2018), Slemrod (2015), or Miethe (2020). The literature draws on discrepancies in international financial statistics (Clausing, 2020; Torslov et al., 2020; Zucman, 2013; Miethe, 2020) or uses microeconomic data for multinational firms (Becker et al., 2020; Johannesson et al., 2017; Miethe, 2020).

Outside tax research, night light data already have been widely used in the literature for its ability to proxy economic activity (see Elvidge et al., 1997; Sutton et al., 2007; Doll et al., 2006; Andersen et al., 2010; Elvidge et al., 2012; Pinkovskiy, 2017). Henderson et al. (2011) is the seminal paper on the use of night lights data to proxy economic activity. Following Henderson et al. (2011), night lights data have been used as a benchmark in order to show that national accounts data is more reliable than household survey data (Pinkovskiy and Sala-i-Martin, 2016), to proxy per capita output in African ethnic territories and to analyse the effects of dividing these territories during the Scramble for Africa (Michalopoulos and Papaioannou, 2014), to proxy incomes of various ethnic groups (Alesina et al., 2016), to show that there might be mismeasurement of national income statistics in some developing countries and to show that in these cases night lights might be more precise (Pinkovskiy, 2017). The construction of night light data is discussed in Baugh et al. (2009), while possible pitfalls are discussed in Doll (2008). Hoopes et al. (2023) use night light data to study whether tax policies in developed nations affect economic activity in developing countries. To the best of our knowledge, our study is the first to use night light data to study the effect of international tax rules.

The remainder of this paper is structured as follows. Section 2 explains tax information exchange agreements. The data used in our study are introduced in Section 3. Section 4 explains the estimation method. Empirical results are presented in Section 5 and robustness checks in Section 6. Finally, Section 7 concludes.

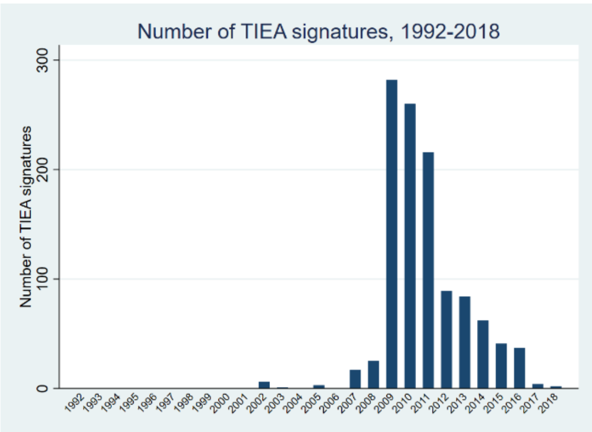
2. Tax information exchange agreements

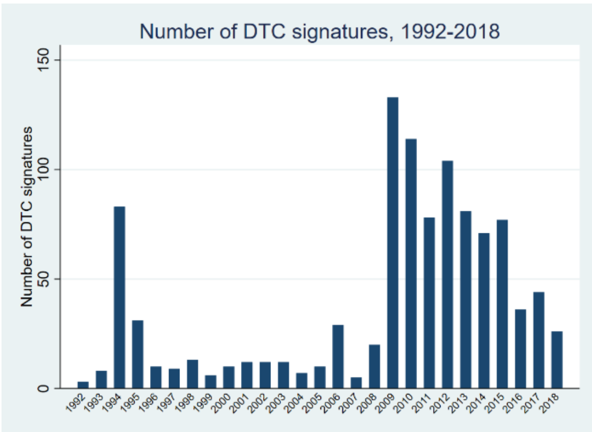
Recent international high-profile initiatives have targeted illicit tax evasion by arm-twisting tax haven countries into agreeing on tax information exchange (OECD, 1998, 2000; Menkhoff and Miethe, 2019). In 2009, the G20 threatened to sanction tax havens with less than 12 tax information exchange treaties (TIEAs).[5] This led to a stark increase in the number of signed treaties (G20, 2009; Menkhoff and Miethe, 2019).

Tax information exchange treaties (TIEAs) allow for bilateral information exchange between the signatory states. Tax information exchange can be demanded from a partner jurisdiction if the information is foreseeably relevant and the identity of the suspected evader is known (Christensen and Tirard, 2016; Menkhoff and Miethe, 2019).

Although this is not their focus, double tax conventions (DTCs) may also allow for tax information exchange. These treaties cover a number of different double taxation issues, which may include tax information exchange. In our analysis, we refer to the universe of TIEAs and relevant DTCs as information on request (IoR) treaties. We also include in our IoR definition the bilateral exchange relationships due to multilateral treaties such as the EU Council Directive 2011-16 or the OECD Convention on Mutual Administrative Assistance in Tax Matters (MC).

By their nature, TIEAs and DTCs only enable tax authorities to exchange information upon request. This was subject to much criticism and in 2014 led to the development of agreements on automatic exchange of information (AEOI) within the framework of the OECD's Common Reporting Standard Multilateral Competent Authority Agreement (CRS). Within this multilateral framework, a bilateral matching process is required so that the technical preconditions for the exchange can be provided. Initially, 44 countries adopted AEOI (OECD, 2016; Menkhoff and Miethe, 2019). We complement our analysis of IoR treaties with the matches on AEOI.





[5] Because of the 12-country threshold, tax havens potentially could have signed only 12 treaties with other tax havens or with economically meaningless countries in order to escape the sanction. However, on average, tax havens in fact entered TIEA relationships with non-havens with whom they have strong economic ties (Bilicka and Fuest, 2014; Menkhoff and Miethe, 2019).

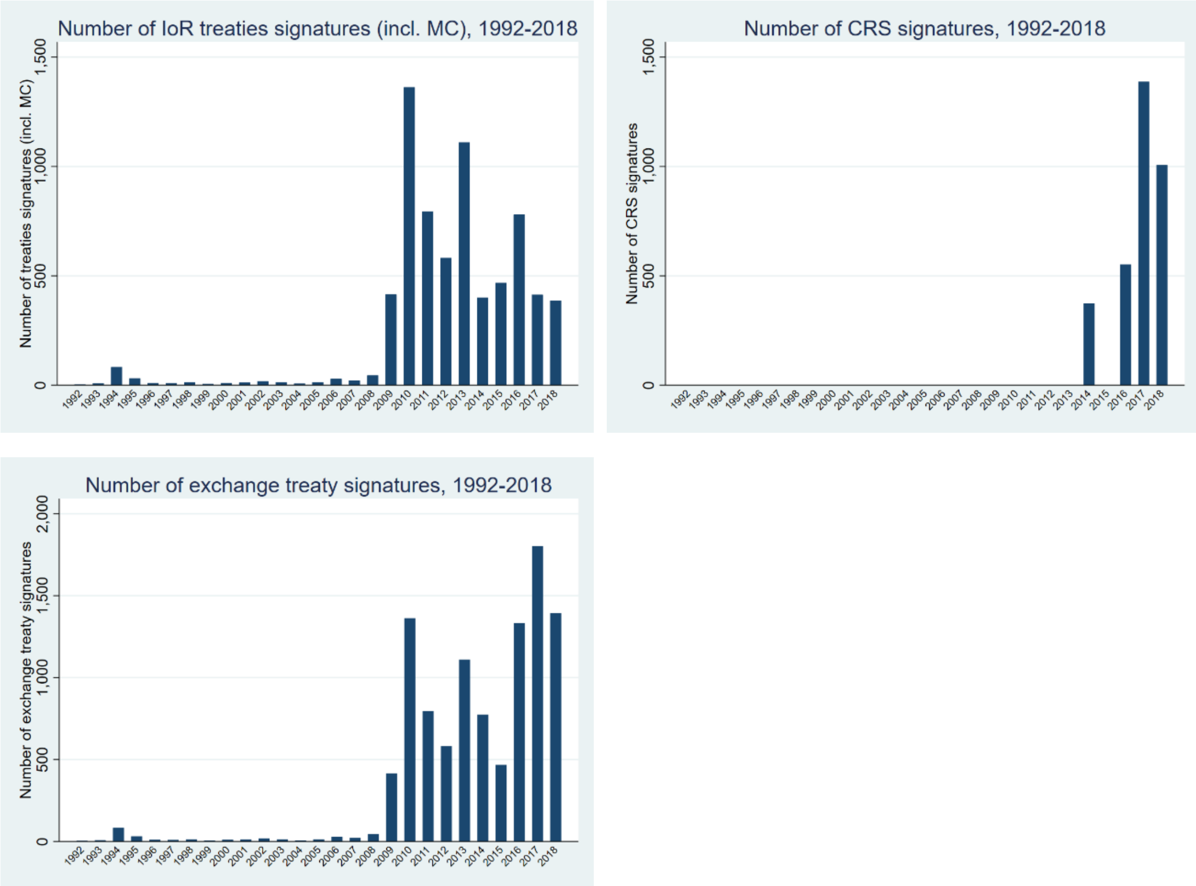


Figure 1: Number of tax information exchange treaty signatures in tax havens by type of treaty, 1992-2018. Own representation based on the OECD Peer Reviews.

Notes: TIEA=tax information exchange agreement, DTC=double tax convention, IoR=TIEA+DTC=information on request treaties, CRS=common reporting standard treaty, exchange treaties=IoR+CRS. If a tax haven jurisdiction joins the CRS, we treat this as if the jurisdiction had concluded bilateral treaties with all other member countries of the CRS.

Figure 1 shows the development of newly signed treaties with tax havens between 1992 and 2018. There was a peak in new signatures of IoR treaties in 2010, with continuous treaty signatures thereafter. Looking at TIEAs and DTCs separately, we observe that DTC signatures have peaked in the 1990s; a second peak coincides with the TIEA peak in the time period 2010-2015. By 2015, new signatures have levelled out. CRS treaties started to be signed in 2014. Adding IoR and CRS treaty signatures, it becomes apparent that they have seen an overall increase since 2010. In recent years, whereas IoR treaty signatures have decreased, CRS treaty signatures have accelerated.[6]

3. Data

3.1. Sample selection

The definition of a tax haven differs across the tax haven literature. However, all definitions require a tax haven to have a low or zero tax rate, at least on some income types. Mostly, tax

[6] Gravity-weighting of exchange treaties or changing the tax haven list lead to closely comparable time patterns.

havens are also required to have strict bank secrecy and low transparency requirements (Menkhoff and Miethe, 2019).[7] Since, for most research questions, erroneously including a non-haven into a tax haven list results in more conservative estimations, empirical papers often use relatively extensive tax haven lists (Menkhoff and Miethe, 2019). We follow this approach. Our sample consists of all tax haven countries obtained by combining the lists of tax havens by Hines (2010), Hebous (2014), Braun and Weichenrieder (2015), Hebous and Lipatov (2014), Rose and Spiegel (2007), Casi et al. (2020), Johannesen et al. (2020), Menkhoff and Miethe (2019), Johannesen and Zucman (2014), Glautier and Bassinger (1987), Hines and Rice (1994), OECD (2000), Dharmapala (2008) and Gravelle (2015). The countries included as tax havens in our study are listed in Appendix A.1, along with the disagreements in the literature over tax havens. Our discussion of empirical results will emphasize on robustness across alternative tax haven lists.

3.2. Night lights data for tax havens

As GDP data for tax havens is often missing, we use satellite data on night light to proxy economic conditions. In particular, the following 11 tax haven countries in our sample do not report GDP data: Anguilla, Cook Islands, Guernsey, Jersey, Montserrat, Niue, Vatican City, British Virgin Islands, Curacao, Gibraltar, and Sint Maarten. Depending on which of the tax haven lists in the literature we use, non-reporting jurisdictions account for between 11% and 25% of all tax haven jurisdictions (see Figures 2 and 3).

[7] While not constitutive, tax havens are commonly associated with high governance indicators, sophisticated communication infrastructure, and few natural resources (Dharmapala, 2008; Dharmapala and Hines, 2009a; Hines, 2010; Menkhoff and Miethe, 2019).

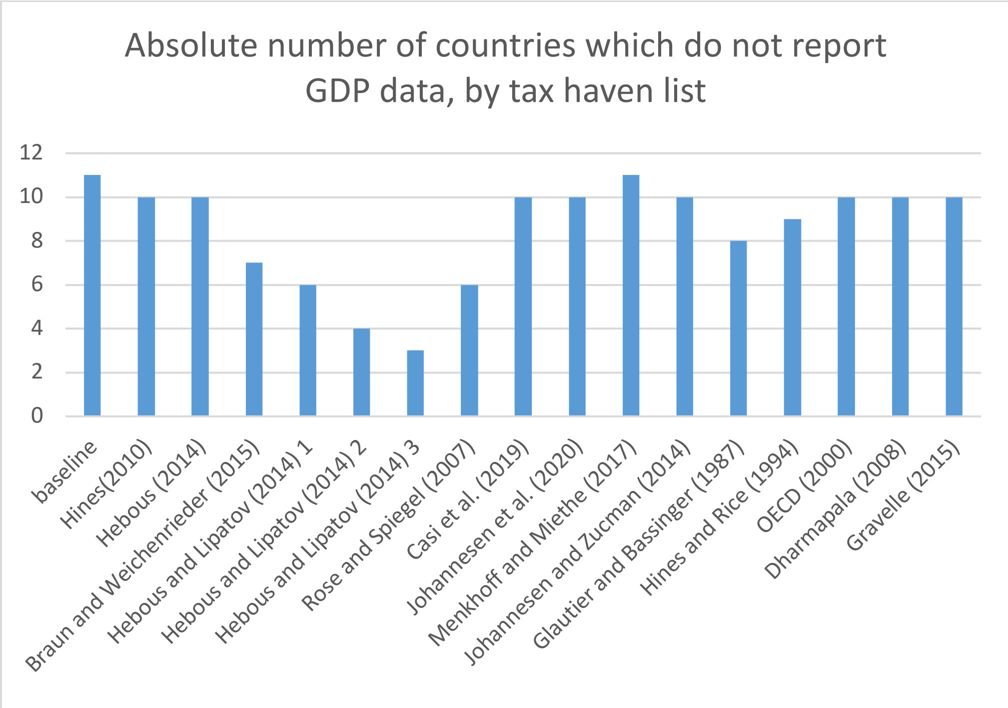


Figure 2: Absolute number of countries that do not report GDP data, by tax haven list. Own representation, based on GDP data from the World Development Indicators (WDI).

Notes: Hebous and Lipatov (2014) use three alternative tax haven lists.

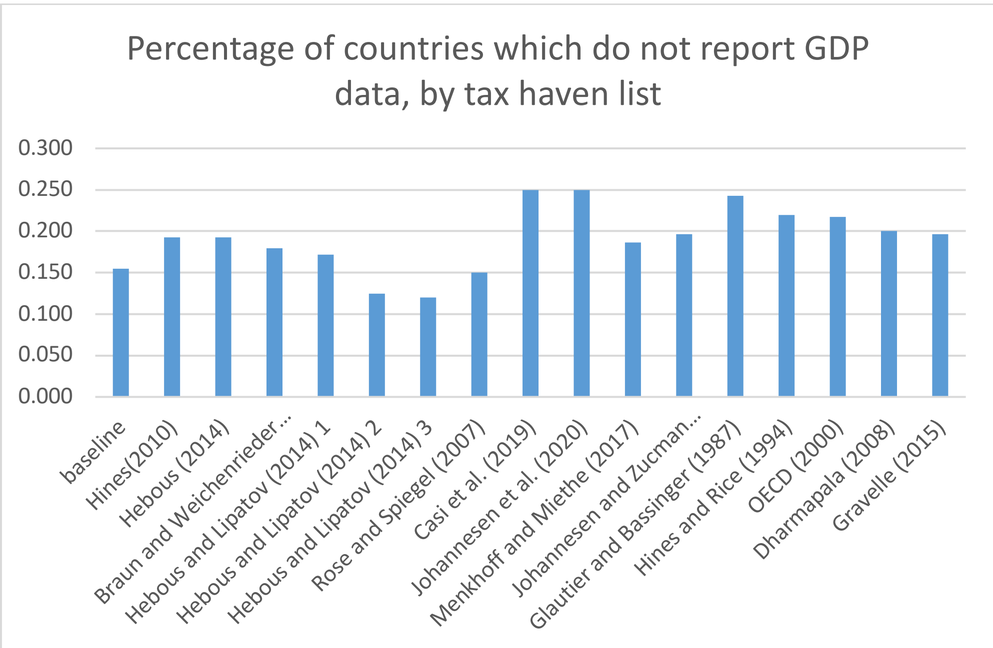


Figure 3: Percentage of countries that do not report GDP data, by tax haven list. Own representation, based on GDP data from the World Bank's World Development Indicators (WDI).

Notes: Hebous and Lipatov (2014) use three alternative tax haven lists.

Tax Haven	Continent	Island	Carribean Island	Former Colony	Colonizer	British overseas territory	French overseas territory	Dutch overseas territory
Anguilla	North America	1	1	1	British	1	0	0
Cook Islands	Oceanien	1	0	1	British	1	0	0
Guernsey	Europe	1	0	0		1	0	0
Jersey	Europe	1	0	0		1	0	0
Montserrat	North America	1	1	1	British	1	0	0
Niue	Oceanien	1	0	1	British	1	0	0
Vatican City	Europe	0	0	0		0	0	0
British Virgin Islands	North America	1	1	1	Dutch, British, Danish, US	1	0	0
Curacao	North America	1	1	1	Spanish, Dutch	0	0	1
Gibraltar	Europe	0	0	1	British	1	0	0
Sint Maarten	North America	1	1	1	Dutch	0	0	0

Table 1: Characteristics of tax havens with missing GDP data.

Table 1 depicts the characteristics of tax havens for which GDP data is missing. Most of them are islands with British heritage. Countries which do not report GDP data tend to rank low on sum of lights and low on geographical size (see Appendix A.2.). These tax havens do not seem to rank significantly high or low on either the number of tax information exchange agreements or on the number of CRS relationships (see Appendix A.2). None of the tax havens without GDP data are in Africa or Asia.

In cases where local GDP data is missing, night light emissions have become a common proxy. The use of night light emissions as a proxy for GDP assumes that Engel curves are stable. (See, e.g., Bils and Klenow, 2001; Costa, 2001; Young, 2012; Donaldson and Storeygard, 2016.)

The hypothesis that night light emissions are a good proxy for economic activity is supported by a vast literature from remote sensing and economics, which has found night light to be highly predictive for economic activities within a given territory (among others, see Doll et al., 2006; Michalopoulos and Papaiannou, 2018).

In a country panel for 1992 to 2008, Henderson et al. (2012) estimate a light-GDP elasticity of 0.28 to 0.32. They do not find evidence of nonlinearity or asymmetry between increases and decreases in night lights[8] (Donaldson and Storeygard, 2016). Martinez (2022) builds on Henderson et al. (2012) to develop a method to measure the potential exaggeration of national GDP statistics by authoritarian governments. On this, see also Trinh, 2019.[9] Unlike GDP

[8] Chen and Nordhaus (2011) provide a somewhat critical view on the proxy quality of night lights data. For a list of early work on night lights at NOAA, see https://ngdc.noaa.gov/eog/pubs_new.html.

[9] To study the expansion of settlements in the US, the academic literature has made use of satellite data on land cover (see. e.g., Burchfield et al., 2006, or Henderson et al., 2012). Related literature shows that night lights reflect human economic activity (see e.g., Croft, 1978; Elvidge et al., 1997; Sutton and Costanza, 2002; Ebener et al.,

statistics, measures of night light are difficult to manipulate by authoritarian governments and should therefore be orthogonal to misreporting errors of GDP.[10]

For those tax haven countries in our sample that do report GDP data, Figure 4 and Table 2 show the relationship between log GDP and log of sum of night lights. When controlling for country-fixed effects, the correlation between night light emissions and GDP (both in logs) is always highly significant irrespective of the exact tax haven list used.

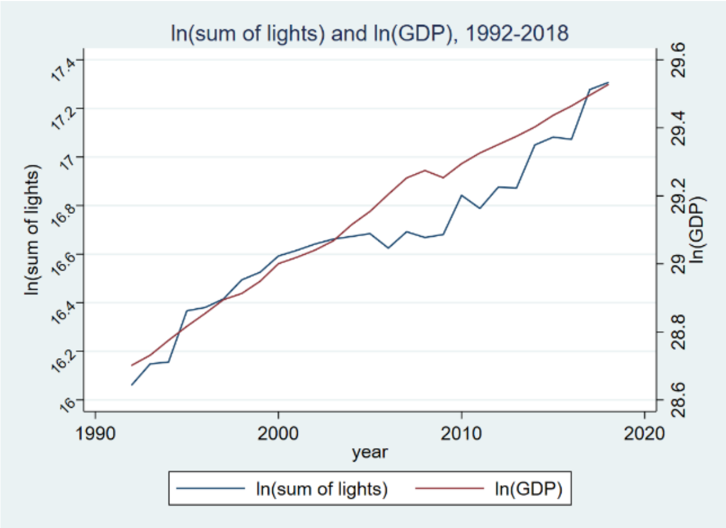


Figure 4: Development of log of lights and log of GDP, 1992-2018.

Notes: Based on the NOAA VIIRS-DMSP Harmonized dataset and WDI GDP data.

	(1) baseline	(2) Hines10	(3) Hebous14	(4) HebLip14(3)	(5) MenkMie17	(6) JohaZu14	(7) OECD2000	(8) Grav15
lnGDP	0.854***	0.681***	0.777***	0.964***	0.752***	0.741***	0.741***	0.677***
	(0.116)	(0.136)	(0.146)	(0.187)	(0.126)	(0.150)	(0.164)	(0.136)
Obs.	1,480	1,013	1,042	541	1,163	1,004	866	1,001
Countries	60	42	42	22	48	41	36	41

Standard errors clustered on country level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Correlation of ln(GDP) and ln(sum of night lights) by tax haven list, 1992-2018

Notes: Based on the NOAA VIIRS-DMSP Harmonized dataset and WDI GDP data. All regressions include country-fixed effects of which coefficients are not reported, but no time-fixed effects. The baseline includes all countries for which GDP data is available (column 1). Further columns include all tax havens with reported GDP date in various tax haven lists: Hines (2010), Hebous (14), Hebous and Lipatov (2014), Menkhoff and Miethe (2019), Johannesen and Zucman (2014), OECD (2000), and Gravelle (2015).

The US military provides the Defense Meterological Satellite Program DMSP, which has served as a data source for much of the literature in development economics (Bertinelli and

2005; Doll et al., 2006; Elvidge et al., 2007; Ghosh et al., 2010) and that the absence of night lights effectively reveal patterns of extreme poverty (see e.g. Elvidge et al. 2009, Yu et al. 2015, Trinh 2019).

[10] Other measures, such as electricity consumption (e.g., used by Wallace, 2016), are more likely to suffer from GDP confounding factors (Trinh, 2019).

Strobl, 2013; Miethe, 2020). Following the DMSP, the Visible Infrared Imaging Radiometer Suite (VIIRS) was developed by the NASA and the NOAA National Geophysics Data Center, improving several of the shortcomings of the DMSP (Miethe, 2020).

In our analysis, we work with the NOAA harmonized DMSP-VIIRS yearly dataset from 1992 to 2018. This dataset matches temporally calibrated DMSP data[11] with non-straylight-corrected VIIRS data[12] (Li et al. 2020). We combine the night lights dataset with geospatial data on national boundaries of the tax havens in our sample[13], where spatial polygons are taken from the Global Administrative Areas dataset.[14] These polygons allow us to calculate the nightlight intensity of each tax haven in each year, creating a yearly time series from 1992 to 2018. Figure 5 shows the yearly growth rates for night light emissions as well as the yearly GDP growth rate in our sample of tax haven jurisdictions from 1992 to 2018. Yearly growth is considerably more dispersed when it comes to night light emissions as shown in the left panel of Figure 5. This said, we should keep in mind that some tax haven jurisdictions are not represented in the right hand panel and that GDP data may be constructed with errors, possibly also some smoothing effects over time.

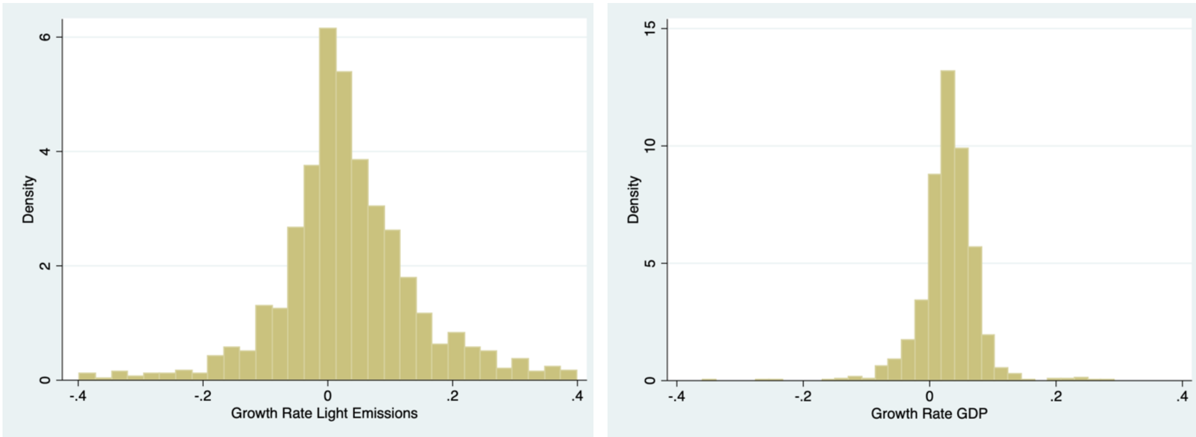


Figure 5: Growth rates of sum of night lights and GDP, 1992-2018.

Notes: Own representation, based on the NOAA VIIRS-DMSP Harmonized dataset. The left panel has been truncated at -0.4 and +0.4.

3.3. Tax information exchange agreement data

We use data from the OECD Peer Reviews on tax information exchange agreements and double tax treaties as well as automatic information exchange treaties. The OECD Peer Reviews are a natural source for tax information exchange agreement data because they can be publicly

[11] This makes sure that DMSP data is temporally consistent (Li et al., 2020).
[12] This means that VIIRS data is cleaned from disturbance due to aurora and temporal lights.
[13] Last accessed on September 9, 2021 at https://payneinstitute.mines.edu/eog.
[14] Last accessed September 9, 2021 at http://www.gadm.org/country.

accessed, they provide relatively recent data, and they give us a comparable definition of tax information exchange treaties (Menkhoff and Miethe, 2019). Following Menkhoff and Miethe (2019), we include only treaties that are reviewed, include paragraphs 4 and 5, and meet the OECD peer review standard.

To take into account the differing relative importance of tax information exchange agreement treaties, we follow Huizinga and Nicodème (2004) and gravity-weigh the IoR treaties as follows:

$$treatysignedgrav_{it} = \frac{\sum_j treatysigned_{ijt} * \overline{Y_J} * D_{ij}^{-2}}{\sum_j \overline{Y_J} * D_{ij}^{-2}}$$

The numerator of the variable $treatysignedgrav_{it}$ captures the distance and income weighted sum of treaty partners. Here, $treatysigned_{ijt}$ is a dummy. By default, it is zero, but changes to the value 1 in the year in which an IoR treaty between a tax haven and a partner country j is signed, as well as in subsequent years. $\overline{Y_\iota}$ captures the GDP of the partner countries in 2010. We select a constant value as GDP may be correlated with the number and importance of treaties signed. This definition also avoids changes of the measure if there is no change in the number of tax information exchange agreements. D_{ij}^{-2} is the inverse of the quadratic distance between capital cities of the tax haven and the partner country, where data is taken from the Geo distance database. The denominator is the GDP and distance weighted sum of all available partner countries with which a tax haven can have an information exchange agreement. This results in values between zero and one for every tax haven's tax information exchange agreement activity in each year. A maximum of 1 would be achieved if a tax haven has a tax information exchange agreement with every possible partner country and 0 if none was signed.

Similarly, for automatic exchange agreements, we gravity-weigh CRS treaties as follows:

$$CRSgrav_{it} = \frac{\sum_j CRSsigned_{ijt} * \overline{Y_\iota} * D_{ij}^{-2}}{\sum_j \overline{Y_J} * D_{ij}^{-2}}$$

where $CRSsigned_{ijt}$ is a dummy taking value 1 if there is a CRS agreement between tax haven i and a partner country j, and 0 otherwise.

Figure 6 illustrates the resulting distribution for these weighted variables for 2018, the latest year in our data. For IoR treaties and the variable $treatysignedgrav_{it}$ we observe a zero in roughly 35% of our 71 jurisdictions, for CRS agreements ($CRSgrav_{it}$) the equivalent number is some 45%. For both variables, the remaining observations populate a wide range between zero and one.

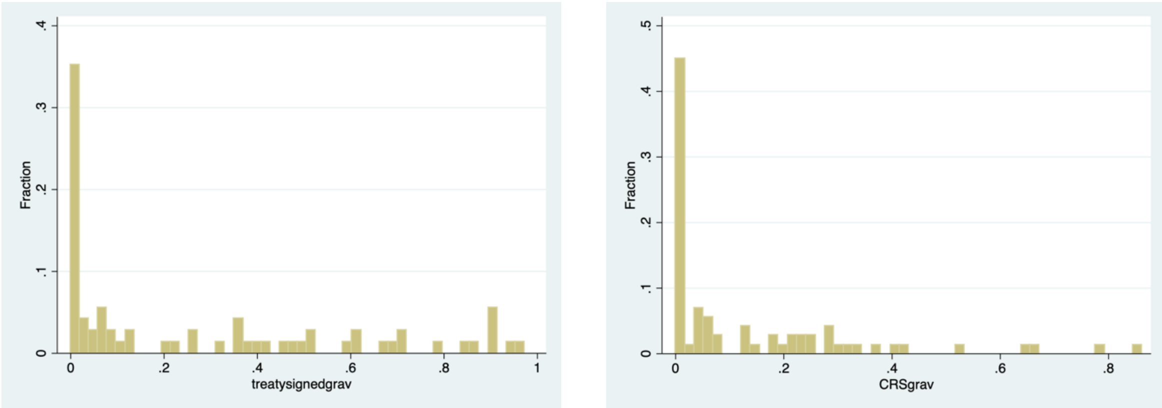


Figure 6: The Distribution of treatysignedgrav and CRSgrav in 2018.

4. Estimation Method

To estimate the effect of tax information exchange agreements on tax haven economic conditions, we regress the log of the sum of night lights on the gravity-weighted number of signed tax information exchange treaties and on controls. Specifically, we estimate the following equation:

$$\ln(lightsum_{it}) = \beta_1 * \mathrm{treatysignedgrav_{it}} + \beta_2 * \mathrm{CRSgrav_{it}} + X_{it} + \delta_t + \mu_i + \alpha_t + VIIRS_t * \mu_i + u_{i,t} \quad (1)$$

$\ln(lightsum_{it})$ is the log of the sum of night lights in tax haven i in year t. The variables of interest are $\mathrm{treatysignedgrav_{it}}$, the number of gravity-weighted IoR treaties in tax haven i in year t, and $\mathrm{CRSgrav_{it}}$, the gravity-weighted number of CRS agreements in tax haven i in year t. In robustness checks we control for ln(population), the governance index, and the corporate tax rate, but decided to leave these variables out in our main specification. The population may be an outcome variable that could be influenced by tax information treaties and the changed economic activity resulting from such treaties.[15] The governance index and the corporate tax rates in tax havens was left out because their inclusion reduced observations, but did not result in significant coefficients for these two variables.

Our econometric analysis has to deal with several issues. First, using fixed effects μ_i allows us to take into account observable and unobservable time-invariant heterogeneities in our observations due to e.g. geography and climate (following Fabian et al., 2019). Second, we

[15] Population data is taken from the Center for International Earth Science Information Network. These data are published in 5-year waves. In robustness checks missing values were interpolated (Fabian et al., 2019).

include year fixed effects δ_t which capture, amongst others, that satellite configurations and sensor technologies change over time and that sensors degenerate during a typically 5-year activity period (Fabian et al., 2019). We further include country specific VIIRS-satellite fixed effects to account for the breaks in the time series due to the change in satellites in 2013.

5. Empirical Results

Table 3 shows our OLS results on the effects of gravity-weighted information exchange treaty signatures on the economic development in tax havens. Economic activity in tax havens is proxied by the log of sum of night lights in tax haven i in year t. While the first column reports results for the full sample, the subsequent columns reflect different tax haven lists that have been proposed in the literature, listed by publication.

The results provide a weakly significant or insignificant result for the treaties that provide for case-by-case exchange of information, $\mathrm{treatysignedgrav}_{\mathrm{it}}$. At the same time, the coefficient for CRSgrav, that indicates the gravity-weighted network of a tax haven's treaties with automatic information exchange, is positive and significant for most lists.

Our variables of interest, $\mathrm{treatysignedgrav}_{\mathrm{it}}$ and $\mathrm{CRSgrav}_{\mathrm{it}}$, are encoded such that they are between zero and one. The value zero applies in the case of no treaties, the value one if treaties with all possible partner countries are concluded. According to the estimates in Table 3, column (1), a move of having no IoR treaties to having an IOR with all the world would increase the sum of night light emissions by 29.5%. In 2018, the standard deviation of treatysignedgrav is .32, hence, a one-standard-deviation increase translates into a 9.4% increase in night light emissions. A drastic change in signed CRS agreements from zero to one would increase night light emissions by 27.1%, a one-standard deviation (in 2018) of *CRSgrav* would lead to a 5.3% increase in luminosity.

Table 4 repeats the same exercise, but, for all tax haven lists, results are derived by using only those country-year observations for which GDP data is available as well. The comparison of Table 3 and Table 3 therefore provides an impression of the effects of omitting or not omitting tax havens with missing national accounts data. Unlike in the full samples, the samples that miss up to 11 jurisdictions lead to a high significance of the IoR information exchange variable, $\mathrm{treatysignedgrav}_{\mathrm{it}}$. Conversely, the automatic exchange variable $\mathrm{CRSgrav}_{\mathrm{it}}$ is less significant in several columns. In the full sample of column (1) in Table 4, both coefficients are higher compared to those found in Table 3.

VARIABLES	(1) baseline	(2) Hines10	(3) Hebous14	(4) HebLip14(3)	(5) MenkMie17	(6) JohaZu14	(7) OECD2000	(8) Grav15
treatysignedgrav	0.295*	0.290	0.360**	0.428	0.308	0.322	0.320	0.312
	(0.165)	(0.222)	(0.178)	(0.286)	(0.186)	(0.196)	(0.238)	(0.221)
CRSgrav	0.271**	0.263	0.359***	0.348***	0.385***	0.408***	0.347*	0.333*
	(0.128)	(0.184)	(0.124)	(0.0814)	(0.126)	(0.127)	(0.194)	(0.192)
Constant	9.679***	8.746***	9.263***	9.694***	9.132***	9.046***	8.448***	8.757***
	(0.0617)	(0.0785)	(0.0793)	(0.131)	(0.0730)	(0.0832)	(0.0887)	(0.0800)
Observations	1,917	1,404	1,404	675	1,566	1,377	1,242	1,377
R-squared	0.733	0.706	0.730	0.770	0.710	0.712	0.692	0.700
Number of countries	71	52	52	25	58	51	46	51

Table 3: Effect of the gravity-weighted number of signed IoR and CRS treaties on ln(sum of night lights), 1992-2018.

*Notes: treatysignedgrav is the gravity-weighted number of IoR treaties that provide for information exchange on request. CRSgrav is the gravity-weighted number of CRS treaties that provide for automatic information exchange. Observations are number of tax haven years. Robust standard errors are clustered at the tax haven-level. *** p<0.01, ** p<0.05, * p<0.1. We include country-fixed effects and year-fixed effects (not reported).*

VARIABLES	(1) baseline	(2) Hines10	(3) Hebous14	(4) HebLip14(3)	(5) MenkMie17	(6) JohaZu14	(7) OECD2000	(8) Grav15
treatysignedgrav	0.395***	0.554***	0.496***	0.441**	0.412***	0.455***	0.565***	0.536***
	(0.127)	(0.183)	(0.139)	(0.208)	(0.149)	(0.160)	(0.207)	(0.184)
CRSgrav	0.268*	0.269	0.350**	0.354***	0.372**	0.396**	0.330	0.315
	(0.156)	(0.275)	(0.157)	(0.0811)	(0.159)	(0.161)	(0.296)	(0.285)
Observations	1,480	1,013	1,042	541	1,163	1,004	866	1,001
R-squared	0.799	0.767	0.808	0.836	0.791	0.790	0.769	0.774
Number of iso3_onum	60	42	42	22	47	41	36	41

Table 4: Effect of the gravity-weighted number of signed IoR and CRS treaties on ln(sum of night lights) for jurisdictions with GDP data, 1992-2018.

*Notes: treatysignedgrav is the gravity-weighted number of IoR treaties that provide for information exchange on request. CRSgrav is the gravity-weighted number of CRS treaties that provide for automatic information exchange. Observations are number of tax haven years. Robust standard errors are clustered at the tax haven-level. *** p<0.01, ** p<0.05, * p<0.1. We include country-fixed effects and year-fixed effects (not reported).*

VARIABLES	(1) baseline	(2) Hines10	(3) Hebous14	(4) HebLip14(3)	(5) MenkMie17	(6) JohaZu14	(7) OECD2000	(8) Grav15
treatysignedgrav	0.0518	0.0688	0.0627	0.0460	0.0249	-0.00392	0.0720	0.0624
	(0.104)	(0.160)	(0.135)	(0.162)	(0.129)	(0.135)	(0.150)	(0.160)
CRSgrav	-0.0266	-0.0583*	-0.0278	0.0131	-0.0271	-0.00991	-0.0518	-0.0580*
	(0.0259)	(0.0323)	(0.0268)	(0.0410)	(0.0281)	(0.0295)	(0.0328)	(0.0325)
Constant	22.91***	22.01***	22.76***	23.22***	22.53***	22.49***	21.75***	22.07***
	(0.0260)	(0.0315)	(0.0358)	(0.0535)	(0.0322)	(0.0330)	(0.0312)	(0.0319)
Observations	1,480	1,013	1,042	541	1,163	1,004	866	1,001
R-squared	0.867	0.850	0.860	0.872	0.859	0.848	0.865	0.856
Number of iso3countries	60	42	42	22	47	41	36	41

Table 5: Effect of the gravity-weighted number of signed IoR and CRS treaties on ln(GDP), 1992-2018.

*Notes: treatysignedgrav is the gravity-weighted number of IoR treaties that provide for information exchange on request. CRSgrav is the gravity-weighted number of CRS treaties that provide for automatic information exchange. Observations are number of tax haven years. Robust standard errors are clustered at the tax haven-level. *** p<0.01, ** p<0.05, * p<0.1. We include country-fixed effects and year-fixed effects (not reported).*

Table 5 shows the same set of regressions, with the natural logarithm of GDP as the left-hand variable. Unlike for the same samples in Table 4, results are almost uniformly insignificant, or weakly significant at best.

Whether we measure economic activity via GDP or night light emissions, our results suggest that more cooperative tax heavens did not fare worse than less cooperative tax havens. The exclusion or inclusion of tax haven jurisdictions without GDP data makes a difference with respect to the exact results. Including those typically smaller jurisdictions, we have a consistently positive and significant effect of case-by-case exchange (IoR), but not so for automatic exchange (CRS). Dropping these 11 jurisdictions tends to yield higher significance levels for automatic exchange, compared to case-by-case exchange.

Our results are not only dependent on the inclusion of tax havens that do not report GDP data. For those jurisdictions that do report GDP, we find that the effect of information exchange is more positive if night light data is used as a measure of economic activity, rather than GDP. The difference in the results may possibly stem from a changed industry structure. If transparency leads to some reduction of the financial sector of cooperative tax havens, workers may be moving to other, more light intensive industries. The possibility that industry structures may affect luminosity has already been mentioned by Henderson et al. (2012, p. 1006).

6. Robustness checks

To check for the robustness of our empirical results, one alternative specification is to take imports of tax haven jurisdictions as our left-hand variable. The idea behind this strategy is that, unlike GDP, import data are more difficult to manipulate as these data are easily double checked by data of partner countries' exports. At the same time, a higher level of imports can be interpreted as a signal for a higher level of welfare. Import (CIF) data is taken from the IMF and measured in millions of US dollars. Unfortunately, the samples shrink considerably when we use exports and imports instead of night light emissions.[16]

[16] The 12 countries for which exports and imports data are not available include: Andorra, Cayman Islands, Cook Islands, Guernsey, Isle of Man, Jersey, Liechtenstein, Monaco, Niue, Turks and Caicos Islands, U.S. Virgin Islands, and British Virgin Islands.

VARIABLES	(1) baseline	(2) Hines10	(3) Hebous14	(4) HebLip14(3)	(5) MenkMie17	(6) JohaZu14	(7) OECD2000	(8) Grav15
treatysignedgrav	0.138	0.123	0.0154	-0.198	0.290	0.107	0.189	0.312
	(0.219)	(0.323)	(0.234)	(0.237)	(0.291)	(0.338)	(0.442)	(0.366)
CRSgrav	-0.185***	-0.0374	-0.177***	-0.175***	-0.167***	-0.165***	-0.129	-0.120
	(0.0471)	(0.149)	(0.0515)	(0.0601)	(0.0500)	(0.0536)	(0.166)	(0.156)
Constant	22.91***	22.01***	22.76***	23.22***	22.53***	22.49***	21.75***	22.07***
	(0.0260)	(0.0315)	(0.0358)	(0.0535)	(0.0322)	(0.0330)	(0.0312)	(0.0319)
Observations	875	473	613	380	623	514	353	488
R-squared	0.836	0.877	0.882	0.904	0.830	0.823	0.773	0.809
Number of countries	48	31	33	18	36	31	26	31

Table 6: Effect of the gravity-weighted number of signed IoR and CRS treaties on ln(imports), 1992-2018.

*Notes: treatysignedgrav is the gravity-weighted number of IoR treaties that provide for information exchange on request. CRSgrav is the gravity-weighted number of CRS treaties that provide for automatic information exchange. Observations are number of tax haven years. Robust standard errors are clustered at the tax haven-level. *** p<0.01, ** p<0.05, * p<0.1. We include country-fixed effects and year-fixed effects (not reported).*

VARIABLES	(1) baseline	(2) Hines10	(3) Hebous14	(4) HebLip14(3)	(5) MenkMie17	(6) JohaZu14	(7) OECD2000	(8) Grav15
treatysignedgrav	0.0933	0.0618	-0.0204	-0.291	0.160	-0.0619	0.178	0.264
	(0.216)	(0.296)	(0.260)	(0.177)	(0.284)	(0.348)	(0.407)	(0.348)
CRSgrav	-0.0578	-0.0461	-0.0616	-0.0399	-0.0686	-0.0594*	-0.0511	-0.0996
	(0.0428)	(0.140)	(0.0490)	(0.0421)	(0.0414)	(0.0319)	(0.110)	(0.137)
Constant	22.91***	22.01***	22.76***	23.22***	22.53***	22.49***	21.75***	22.07***
	(0.0260)	(0.0315)	(0.0358)	(0.0535)	(0.0322)	(0.0330)	(0.0312)	(0.0319)
Observations	875	473	613	380	623	514	353	488
R-squared	0.836	0.877	0.882	0.904	0.830	0.823	0.773	0.809
Number of countries	48	31	33	18	36	31	26	31

Table 7: Effect of the gravity-weighted number of signed IoR and CRS treaties on ln(exports), 1992-2018.

*Notes: treatysignedgrav is the gravity-weighted number of IoR treaties that provide for information exchange on request. CRSgrav is the gravity-weighted number of CRS treaties that provide for automatic information exchange. Observations are number of tax haven years. Robust standard errors are clustered at the tax haven-level. *** p<0.01, ** p<0.05, * p<0.1. We include country-fixed effects and year-fixed effects (not reported).*

VARIABLES	(1) baseline	(2) Hines10	(3) Hebous14	(4) HebLip14(3)	(5) MenkMie17	(6) JohaZu14	(7) OECD2000	(8) Grav15
totnum_treatysignedgrav	0.0524	0.0883	0.0870	-0.121	0.158	0.0575	-0.215	0.0883
	(0.120)	(0.212)	(0.134)	(0.107)	(0.113)	(0.155)	(0.199)	(0.212)
totnum_CRSgrav	-0.159	-0.161*	-0.181	-0.620	-0.116	-0.104	-0.137*	-0.161*
	(0.114)	(0.0760)	(0.116)	(0.402)	(0.110)	(0.0964)	(0.0592)	(0.0760)
Constant	11.52***	10.20***	11.29***	13.04***	11.12***	10.91***	10.02***	10.20***
	(0.105)	(0.0515)	(0.114)	(0.250)	(0.0745)	(0.0818)	(0.0774)	(0.0515)
Observations	351	216	324	135	297	270	162	216
R-squared	0.847	0.851	0.853	0.889	0.848	0.853	0.902	0.851
Number of countries	13	8	12	5	11	10	6	8

Table 8: Effect of the deposit-weighted number of signed IoR and CRS treaties on ln(sum), 1992-2018.

*Notes: treatysignedgrav is the deposit-weighted number of IoR treaties that provide for information exchange on request. CRSgrav is the deposit-weighted number of CRS treaties that provide for automatic information exchange. Observations are number of tax haven years. Robust standard errors are clustered at the tax haven-level. *** p<0.01, ** p<0.05, * p<0.1. We include country-fixed effects and year-fixed effects (not reported). Due to the lack of data availability, all jurisdictions except Austria, Belgium, Chile, Guernsey, Hong Kong, Ireland, Isle of Man, Jersey, Luxembourg, Macao, the Netherlands, Philippines, and Switzerland have to be dropped.*

This said, the signing of automatic information exchange treaties seems to be significantly negatively correlated with imports in Table 6, which could be interpreted as a negative effect on the economy of more cooperative tax-havens. At the same time, there is no significant effect of case-by-case information exchange. Moreover, both measures are insignificantly correlated with the log of exports in Table 7.

As a further variation, we change the weighting of our treaty variables. Instead of gravity-weighting the treaty variables, we weigh by bilateral cross-border deposits using disaggregated quarterly data from the Bank for International Settlements (BIS) on deposits held by individuals and entities that are not residents of the country where the reporting bank is located (Casi et al., 2020).

Our results remain positive, but insignificant, for case-by-case exchange treaties. Coefficients for automatic exchange are negative, but mostly insignificant (see Table 8). These inconclusive results may be due to the fact that the use of BIS data shrinks our sample from a maximum of 71 tax haven countries to a maximum of only 13 tax haven countries, including Austria, Belgium, Chile, Guernsey, Hong Kong, Ireland, Isle of Man, Jersey, Luxembourg, Macao, the Netherlands, Philippines, and Switzerland.

In addition, we test whether selecting only the most credible treaties changes our results. In

Table 9, we consecutively exclude treaties which do not include paragraphs 4 and 5 but were reviewed by the OECD and met the standard (column 1), treaties which were not reviewed at the time of our analysis (column 2), and treaties which were reviewed but did not meet the standard (column 3).[17] Our results remain robust.

[17] See Menkhoff and Miethe (2019) for a similar classification of treaties.

VARIABLES	(1) no para4/5 baseline	(2) +not reviewed baseline	(3) +not standard baseline
treatysignedgrav	0.280*	0.280*	0.322**
	(0.157)	(0.157)	(0.152)
CRSgrav	0.271**	0.271**	0.270**
	(0.128)	(0.128)	(0.127)
Constant	10.15***	10.15***	10.14***
	(0.0488)	(0.0488)	(0.0501)
Observations	1,917	1,917	1,917
R-squared	0.733	0.733	0.734
Number of countries	71	71	71

Table 9: Robustness to different treaty definitions.

*Notes: Effect of the gravity-weighted number of signed CRS treaties and gravity-weighted CRS treaties on ln(sum of night lights), 1992-2018. Column 1 excludes treaties which do not include paragraphs 4 and 5 but were reviewed by the OECD and meet the standard. Column 2 additionally excludes treaties which were not reviewed at the time of the analysis. Column 3 additionally excludes treaties which were reviewed but did not meet the standard. Observations are number of tax haven years. Robust standard errors are clustered at the tax haven-level. *** p<0.01, ** p<0.05, * p<0.1. We include tax haven-fixed effects and year-fixed effects (not reported).*

Finally, Appendices A.3 and A.4 provide further information on robustness by illustrating results from estimates leaving out each country (Figure 7) and from estimates in Table 13 leaving out the years 2008-2009 of the financial crisis.

7. Conclusion

In recent decades, the OECD has undertaken considerable efforts through its high-profile initiative to tackle bank secrecy, tax evasion, and tax havens. In particular, the OECD has induced tax haven jurisdictions to conclude tax information exchange agreements on request as well as automatic exchange of information treaties under its Common Reporting Standard. TIEA and DTC signatures saw a peak in 2010, with new signatures also continuing after this. Multilateral CRS treaties started to be signed in 2014.

So far, the effects of these treaties on tax haven welfare have not been explored in the literature. We analyze the economic development of various tax havens that concluded more versus less tax information exchange treaties. Because GDP data for tax havens is absent for a large number of small, but nevertheless important tax haven jurisdictions, we use the NOAA VIIRS-DMSP harmonized yearly night lights dataset from 1992 to 2018 as a proxy for economic conditions.

Depending on the particular tax haven list, night lights data allow us to increase coverage of tax havens by up to 25% compared to using GDP data.

We conclude from our empirical analysis that more cooperative tax havens do not seem to have suffered economically from signing tax information exchange agreements. Tax haven jurisdictions which signed a greater number of tax agreements (weighted for economic significance) tended to experience more growth in night lights emissions than tax havens with fewer agreements.

When we measure economic activity by GDP, our results suggest insignificant effects of tax information exchange treaties on economic development. Only if we look at the amount of imports, we see a negative correlation with the weighted number of information exchange treaties.

Our results using night light data should be interpreted with care. While our panel regressions correct for country heterogeneity via country-fixed effects, the conclusion of tax information exchange treaties may have been more attractive for jurisdictions that anticipated these treaties do little harm to their business model as a tax haven, which could imply endogeneity issues.

Our paper suggests that cooperative tax havens may not have benefitted in terms of GDP growth, but have gained in luminosity. This could possibly point towards a change in industry structure, away from financial and legal services towards more light intensive manufacturing.

Despite these possible caveats, our paper suggests that more cooperative and transparent tax havens so far did not suffer reduced economic growth.

8. Appendix

Appendix A.1 Comparison of different tax haven lists

Country	Hines (2010)	Hebous (2014)	Braun/Weichenrieder (2015)	Hebous /Lipatov (2014) 1	Hebous /Lipatov (2014) 2	Hebous /Lipatov (2014) 3	Rose /Spiegel (2007)	Casi et al. (2020)	Johannesen et al. (2020)	Menkhoff / Miethe (2017)	Johannesen /Zucman (2014)	Glautier /Bassinger (1987)	Hines /Rice (1994)	OECD (2000)	Dharmapala (2008)	Gravelle (2015)
Andorra	1	1	1	0	0	0	1	1	1	1	1	0	1	1	1	1
Anguilla	1	1	1	0	0	0	0	1	1	1	1	0	1	1	1	1
Antigua and Barbuda	1	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1
Aruba	1	1	1	0	0	0	1	1	1	1	1	0	0	1	1	1
Austria	0	1	0	1	0	1	0	0	0	1	1	1	0	0	0	0
Bahamas	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Bahrain	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Barbados	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
Belgium	0	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0
Belize	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
Bermuda	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1
British Virgin Islands	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
Brunei	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Cayman Islands	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1
Chile	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0
Cook Islands	1	1	0	0	0	0	0	1	1	1	1	1	1	1	1	1
Costa Rica	1	1	1	1	1	1	1	0	0	1	1	1	0	0	0	1
Curacao	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Cyprus	1	0	0	1	1	0	1	0	0	1	1	1	1	1	1	1
Djibouti	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Dominica	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
Gibraltar	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Grenada	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1
Guatemala	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Guernsey	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
Holy See	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Hong Kong	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1
Ireland	1	1	0	0	0	0	0	0	0	1	0	1	1	0	1	1
Isle of Man	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
Israel	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0
Jersey	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
Jordan	1	0	0	0	0	0	0	0	0	1	0	0	1	0	1	1
Kuwait	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0
Lebanon	1	1	1	0	0	0	1	0	0	1	0	0	1	0	1	1
Liberia	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Liechtenstein	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Luxembourg	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1
Macao	1	1	1	1	1	0	1	0	0	1	1	0	1	0	1	1
Malaysia	0	1	0	1	1	1	1	0	0	1	1	0	0	0	0	0
Maldives	1	0	0	0	0	0	0	1	1	1	0	0	1	1	1	1
Malta	1	0	0	1	1	0	1	0	0	1	1	0	1	1	1	1
Marshall Islands	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
Mauritius	1	1	1	1	1	0	1	0	0	1	0	0	0	1	1	1
Micronesia	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Monaco	1	1	0	0	0	0	1	1	1	1	1	0	1	1	1	1
Montserrat	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1
Morocco	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0
Nauru	1	1	1	0	0	0	0	1	1	1	1	0	0	1	1	1
Netherlands	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Niue	1	1	0	0	0	0	0	1	1	1	1	0	0	1	1	1
Oman	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0
Palau	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Panama	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Philippines	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0
Russia	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Samoa	1	1	1	0	0	0	0	1	1	1	1	0	0	1	1	1
San Marino	1	1	1	0	0	1	0	0	0	1	1	0	0	1	1	1
Seychelles	1	0	0	0	0	0	0	1	1	1	1	0	0	1	1	1
Singapore	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sint Maarten	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
St. Kitts and Nevis	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
St. Lucia	1	1	1	0	0	0	0	1	1	1	1	0	1	1	1	1
St. Vincent and the Grenadines	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1
Switzerland	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1
Thailand	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0
Tonga	1	0	0	0	0	0	0	1	1	1	0	0	0	1	1	1
Trinidad and Tobago	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
Turks and Caicos Islands	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1
United Arab Emirates	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Uruguay	0	1	1	1	1	1	1	0	0	1	1	0	0	0	0	0
US Virgin Islands	0	0	0	0	0	0	0	1	1	1	1	0	0	1	1	1

Vanuatu	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1

Table 10: Alternative tax haven lists.

Notes: Curacao and Sint Maarten are combined and listed as the "Netherlands Antilles" in some publications. However, on 10 October 2010 they were officially separated. Guernsey and Jersey are combined and listed as the "Channel Islands" in some publications.

Appendix A.2. Characteristics of tax havens which do not report GDP data

Country	rank_lights	rank_area	rank_lightsarea
Curacao	36	44	18
Jersey	41	60	15
Guernsey	49	62	17
British Virgin Islands	54	58	34
Sint Maarten	55	66	5
Anguilla	58	63	26
Montserrat	64	61	45
Gibraltar	65	69	6
Cook Islands	66	56	58
Niue	71	55	69

Table 11: Rank by lights and area for tax haven countries.

Notes: Own representation based on NOAA VIIRS-DMSP Harmonized dataset and WDI GDP data. rank_lights is the tax haven's rank by sum of lights; rank_area is the tax haven's rank by area and rank_lightsarea is the tax haven's rank by mean lights.

Country	rank_treaties	TIEAsigned	DTCsigned	MCsigned	CRS	treatysigned
Guernsey	17	60	12	69	66	141
Jersey	21,5	40	12	86	67	138
Montserrat	34	12	1	114	62	127
British Virgin Islands	38	27	0	99	65	126
Curacao	38	21	3	102	68	126
Niue	42	8	0	117	26	125
Sint Maarten	44	21	1	102	0	124
Gibraltar	45.5	39	0	84	61	123
Anguilla	47	34	0	88	52	122
Cook Islands	57	18	0	0	69	18

Table 12: Rank by number of IoR treaties signed for tax haven countries.

Notes: Based on OECD Peer Reviews and WDI GDP data. rank_treaties is the tax haven's rank by number of IoR treaties, TIEAsigned is the number of signed TIEAs, DTCsigned is the number of signed DTCs, MCsigned is the number of MC partners, CRS is the number of CRS treaties and treatysigned is the number of IoR treaties. All ranks of year 2018.

Appendix A.3 Robustness to dropping one country

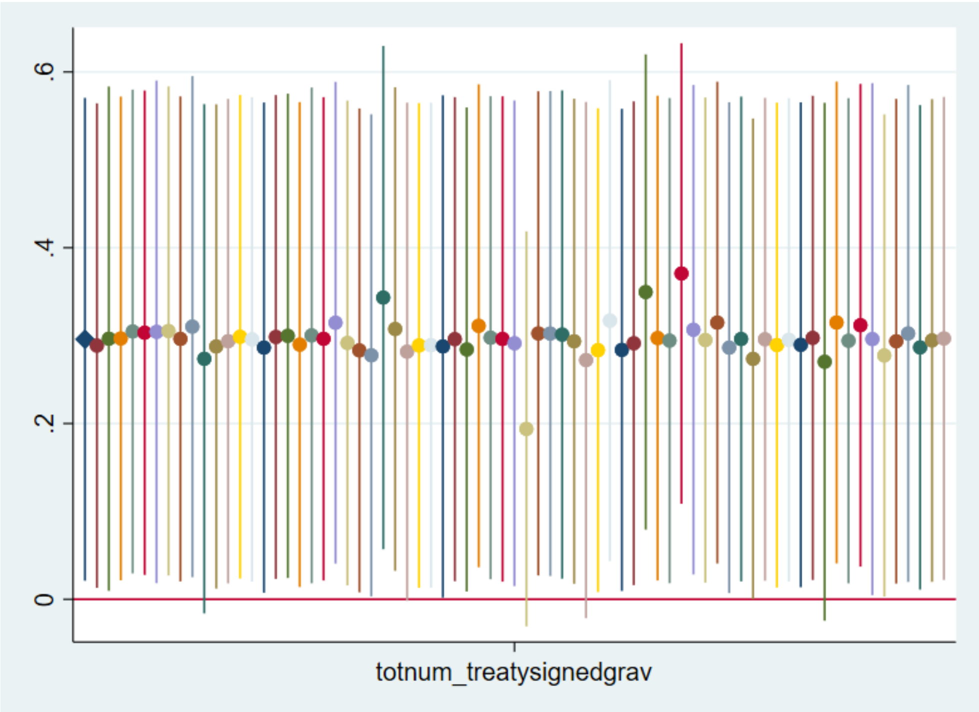


Figure 7: Robustness to dropping one country. Effect of the gravity-weighted number of signed IoR treaties on ln(sum of night lights), 1992-2018.

Notes: This figure reports estimates for the baseline regression without controls. Totnum_treatysignedgrav is the gravity-weighted number of IoR treaties. Confidence intervals are shown at the 90% level.

A.4. Robustness to exclusion of years 2008-2009

VARIABLES	(1) baseline	(2) Hines10	(3) Hebous14	(4) HebLip14(3)	(5) MenkMie17	(6) JohaZu14	(7) OECD2000	(8) Grav15
treatysignedgrav	0.327*	0.321	0.396*	0.495	0.340	0.360	0.357	0.344
	(0.183)	(0.249)	(0.200)	(0.325)	(0.208)	(0.220)	(0.266)	(0.248)
CRSgrav	0.270**	0.262	0.359***	0.347***	0.384***	0.407***	0.346*	0.332*
	(0.128)	(0.184)	(0.124)	(0.0823)	(0.126)	(0.128)	(0.194)	(0.192)
Constant	9.683***	8.750***	9.264***	9.665***	9.135***	9.047***	8.450***	8.761***
	(0.0623)	(0.0792)	(0.0803)	(0.137)	(0.0737)	(0.0840)	(0.0892)	(0.0806)
Observations	1,775	1,300	1,300	625	1,450	1,275	1,150	1,275
R-squared	0.749	0.722	0.745	0.789	0.727	0.727	0.709	0.716
Number of countries	71	52	52	25	58	51	46	51

Table 13: Effect of the gravity-weighted number of signed IoR and CRS treaties on ln(sum of night lights), exclusion of 2008-2009

*Notes: treatysignedgrav is the gravity-weighted number of IoR treaties that provide for information exchange on request. CRSgrav is the gravity-weighted number of CRS treaties that provide for automatic information exchange. Observations are number of tax haven years. Robust standard errors are clustered at the tax haven-level. *** p<0.01, ** p<0.05, * p<0.1. We include country-fixed effects and year-fixed effects (not reported).*

References

Alesina, A., Michalopoulos, S., and Papaioannou, E., 2016. Ethnic Inequality. *Journal of Political Economy*, *124(2),* 428-488.

Alstadsæter, A., Johannesen, N., and Zucman, G., 2018. Who Owns the Wealth in Tax Havens? Macro Evidence and Implications for Global Inequality. *Journal of Public Economics*, *162*, 89-100.

Andersen, J., Johannesen, N., and Rijkers, B., 2020. Elite Capture of Foreign Aid: Evidence from Offshore Bank Accounts. *Journal of Political Economy, 130(2),* 388-425.

Andersen, J., Johannesen, N., Lassen, D., and Paltseva, E., 2017. Petro Rents, Political Institutions, and Hidden Wealth: Evidence from Offshore Bank Accounts. *Journal of the European Economic Association, 15(4),* 818-860.

Anderson, P., Baugh, K., Elvidge, C., Ghosh, T., Sharolyn, J., and Sutton, C., 2012. The Night Light Development Index (NLDI): A Spatially Explicit Measure of Human Development from Satellite Data. *Social Geography, 7(1),* 23-35.

Anderson, S., Baugh, K., Elvidge, C., Gosh, T., Powell, R., and Sutton, P., 2010. Shedding Light on the Global Distribution of Economic Activity. *Open Geography Journal, 3*, 147-160.

Baugh, K., Davis, E., Elvidge, C., Kihn, E., and Kroehl, H., 1997. Mapping City Lights with Nighttime Data from the DMSP Operational Linescan System. *Photogrammetric Engineering & Remote Sensing, 63(6),* 727-734.

Baugh, K., Elvidge, C., Ghosh, T., and Ziskin, D., 2009. Development of a 2009 Stable Lights Product Using DMSP-OLS Data. *Proceedings of the 30th Asia–Pacific Advanced Network Meeting, 30,* 114.

Becker, J., Johannesen, N., and Riedel, N., 2020. Taxation and the Allocation of Risk Inside the Multinational Firm. *Journal of Public Economics*, *183*, 104138.

Beer, S., de Mooij, R., and Liu, L., 2020. International Corporate Tax Avoidance: A Review of the Channels, Magnitudes, and Blind Spots. *Journal of Economic Surveys*, *34(3)*, 660-688.

Bilicka, K., and Fuest, C., 2013. With Which Countries Do Tax Havens Share Information?. *International Tax and Public Finance*, *21(2),* 175-197.

Bils, M., and Klenow, P., 2001. Quantifying Quality Growth. *American Economic Review*, *91(4)*, 1006-1030.

Braun, J. and Weichenrieder, A., 2015. Does Exchange of Information between Tax Authorities Influence Multinationals' Use of Tax Havens?, *SAFE Working Paper No.89*.

Burchfield, M., Overman, H., Puga, D., and Turner, M., 2006. Causes of Sprawl: A Portrait from Space. *Quarterly Journal of Economics*, *121(2)*, 587-633.

Capital Economics, 2017. Creating Value: The BVI's global contribution. *BVI Finance Limited,* in: https://www.bviglobalimpact.com/media-centre/creating-value-the-bvis-global-contribution (Last accessed: 2022-08-01).

Casi, E., Spengel, C., and Stage, B., 2020. Cross-border Tax Evasion after the Common Reporting Standard: Game Over?. *Journal of Public Economics*, *190*, 104240.

Cavallo, E., Galiani, S., Noy, I., and Pantano, J., 2013. Catastrophic Natural Disasters and Economic Growth. *Review of Economics and Statistics*, *95(5),* 1549-1561.

Chen, X., and Nordhaus, W., 2010. The Value of Luminosity Data as a Proxy for Economic Statistics. *NBER Working Papers No. 16317*.

Chen, X., and Nordhaus, W., 2011. Using Luminosity Data as a Proxy for Economic Statistics. *Proceedings of the National Academy of Sciences*, *108(21),* 8589-859.

Chen, X., and Nordhaus, W., 2016. Global Gridded Geographically Based Economic Data (G-Econ), *NASA Socioeconomic Data and Applications Center (SEDAC)*, New York, NY.

Christiaensen, L., Loayza, N., Olaberria, E., and Rigolini, J., 2012. Natural Disasters and Growth: Going Beyond the Averages. *World Development*, *40(7),* 1317-1336.

Christensen, H., and Tirard, J., 2016. The Amazing Development of Exchange of Information in Tax Matters: From Double Tax Treaties to FATCA and the CRS. *Trusts & Trustees*, *22(8),* 898-922.

Clausing, K., 2020. Profit Shifting Before and After the Tax Cuts and Jobs Act. *National Tax Journal*, *73(4),* 1233-1266.

Clifford, S., 2019. Taxing Multinationals Beyond Borders: Financial and Locational Responses to CFC rules. *Journal of Public Economics*, *173*, 44-71.

Costa, D., 2001. Estimating Real Income in the United States from 1888 to 1994: Correcting CPI Bias Using Engel Curves. *Journal of Political Economy, 109(6),* 1288-1310.

Croft, T., 1978. Nighttime Images of the Earth from Space. *Scientific American*, *239(1),* 86-98.

Damgaard, J., Elkjaer, T., and Johannesen, N., 2019. What Is Real and What Is Not in the Global FDI Network?. *IMF Working Paper WP/19/274.*

de Mooij, R., Prihardini, A., Pflugbeil, A., and Stavrev, E., 2020. International Taxation and Luxembourg's Economy*, IMF Working Paper WP/20/264.*

Deaton, A., 2005. Measuring Poverty in a Growing World (or Measuring Growth in a Poor World). *Review of Economics and Statistics, 87(1),* 1-19.

Dharmapala, D., 2008. What Problems and Opportunities Are Created by Tax Havens?. *Oxford Review of Economic Policy*, *24(4),* 661-679.

Dharmapala, D., and Hines, J., 2009. Which Countries Become Tax Havens?. *Journal of Public Economics*, *93(9-10),* 1058-1068.

Dharmapala, D., Foley, C., and Forbes, K., 2011. Watch What I do, Not What I Say: The Unintended Consequences of the Homeland Investment Act. *Journal of Finance*, *66(3),* 753-787.

Doll, C., 2008. CIESIN thematic guide to night-time light remote sensing and its applications. Center for International Earth Science Information Network of Columbia University, Palisades, NY.

Doll, C., Muller, J., and Morley, J., 2006. Mapping Regional Economic Activity from Night-time Light Satellite Imagery. *Ecological Economics*, *57(1)*, 75-92.

Donaldson, D., and Storeygard, A., 2016. The View from Above: Applications of Satellite Data in Economics. *Journal of Economic Perspectives*, *30(4),* 171-198.

Ebener, S., Elvidge, C., Murray, C., and Tandon, A. 2005. From Wealth to Health: Modeling the Distribution of Income per Capita at the Sub-National Level Using Night- Time Light Imagery. *International Journal of Health Geographics*, *4(5)*, 1-17.

Elvidge, C., Baugh, K., Kihn, E., Kroehl, H., Davis, E., and Davis, C., 1997. Relation between Satellite Observed Visible-near Infrared Emissions, Population, Economic Activity and Electric Power Consumption. *International Journal of Remote Sensing*, *18(6),* 1373-1379.

Elvidge, C., Ghosh, T., and Sutton, P., 2007. Estimation of Gross Domestic Product at Sub-national Scales Using Nighttime Satellite Imagery. *International Journal of Ecological Economics & Statistics*, *8(S07),* 5-21.

Elvidge, C., Ziskin, D., Baugh, K., Tuttle, B., Ghosh, T., Pack, D., Erwin, E., and Zhizhin, M., 2009. A Fifteen Year Record of Global Natural Gas Flaring Derived from Satellite Data. *Energies*, *2(3),* 595-622.

Fabian, M., Lessmann, C., and Sofke, T., 2019. Natural Disasters and Regional Development – The Case of Earthquakes. *CESifo Working Paper 7511*.

Felbermayr, G. and Gröschl, J., 2013. Natural Disasters and the Effect of Trade on Income: A New Panel IV Approach. *European Economic Review*, *58*, 18-30.

Felbermayr, G. and Gröschl, J., 2014. Naturally Negative: The Growth Effects of Natural Disasters. *Journal of Development Economics*, *111*, 92-106.

G20 (2009). London Summit Communiqué. *Group of 20 Research Group*, London.

Gennaioli, N., La Porta, R., Lopez De Silanes, F., and Shleifer, F., 2014. Growth in Regions. *Journal of Economic Growth*, *19(3),* 259-309.
Gravelle, J., 2015. Tax Havens: International Tax Avoidance and Evasion. *National Tax Journal*, *62(4),* 727-753.
Hanlon, M., Maydew, E., and Thornock, J., 2015. Taking the Long Way Home: US Tax Evasion and Offshore Investments in US Equity and Debt Markets. *Journal of Finance*, *70(1),* 257-287.
Hebous, S., and Lipatov, V., 2014. A Journey from a Corruption Port to a Tax Haven. *Journal of Comparative Economics*, *42(3),* 739-754.
Hebous, S., 2014. Money at the Docks of Tax Havens: A Guide. *FinanzArchiv/ Public Finance Analysis*, *70(3),* 458-487.
Hines, J., 2010. Treasure Islands. *Journal of Economic Perspectives*, *24(4),* 103-126.
Heckemeyer, J., and Hemmerich, A., 2020. Information Exchange and Tax Haven Investment in OECD Securities Markets. *National Tax Journal*, *73(2),* 291-330.
Henderson, J., Squires, T., Storeygard, A., and Weil, D., 2017. The Global Distribution of Economic Activity: Nature, History, and the Role of Trade. *Quarterly Journal of Economics*, *133(1),* 357-406.
Henderson, J., Storeygard, A., and Weil, D., 2011. A Bright Idea for Measuring Economic Growth. *American Economic Review*, *101(3),* 194-199.
Henderson, J., Storeygard, A., and Weil, D., 2012. Measuring Economic Growth from Outer Space. *American Economic Review*, *102(2),* 994-1028.
Hoopes, J. L., Klein, D., Lester, R., and Olbert, M., 2023. Corporate Tax Policy in Developed Countries and Economic Activity in Africa. *Stanford University Graduate School of Business Research Paper No. 4254414.*
Huizinga, H., and Nicodème, G., 2004. Are International Deposits Tax-driven. *Journal of Public Economics*, *88(6),* 1093-1118.
Jerven, M., 2013. Poor Numbers: How We Are Misled by African Development Statistics and What To Do About It. *Cornell University Press,* Ithaka, NY.
Johannesen, N., 2014. Tax Evasion and Swiss Bank Deposits. *Journal of Public Economics*, *111*, 46-62.
Johannesen, N., Langetieg, P., Reck, D., Risch, M., and Slemrod, J., 2020. Taxing Hidden Wealth: The Consequences of US Enforcement Initiatives on Evasive Foreign Accounts. *American Economic Journal: Economic Policy*, *12(3),* 312-346.
Johansson, A., Menon, C., Skeie, Ø., and Sorbe, S., 2017. Tax Planning by Multinational Firms: Firm-level Evidence from a Cross-country Database. *OECD Economics Department Working Papers No. 1355*.
Johannesen, N., and Zucman, G., 2014. The End of Bank Secrecy? An Evaluation of the G20 Tax Haven Crackdown. *American Economic Journal: Economic Policy*, *6(1),* 65-91.
Klomp, J., 2016. Economic Development and Natural Disasters: A Satellite Data Analysis. *Global Environmental Change*, *36*, 67-88.
Konrad, K., and Stolper, T., 2016. Coordination and the Fight Against Tax Havens. *Journal of International Economics*, *103*, 96-107.
Kudrle, R., 2008. The OECD's Harmful Tax Competition Initiative and the Tax Havens: From Bombshell to Damp Squib. *Global Economy Journal*, *8(1),* 1850128.
Lane, P., and Milesi-Ferretti, G., 2017. International Financial Integration in the Aftermath of the Global Financial Crisis. *IMF Working Paper 17/115*.
Langenmayr, D., 2017. Voluntary Disclosure of Evaded Taxes – Increasing Revenue, or Increasing Incentives to Evade?. *Journal of Public Economics*, *151*, 110-125.
Lessmann, C., and Seidel, A., 2017. Regional Inequality, Convergence, and its Determinants – A View From Outer Space. *European Economic Review*, *92*, 110-132.

Lessmann, C., 2014. Spatial Inequality and Development - Is There an Inverted-U Relationship?. *Journal of Development Economics*, *106*, 35-51.
Li, X., Zhou, Y., Zhao, M., and Zhao, X., 2020. A Harmonized Global Nighttime Light Dataset 1992–2018. *Scientific Data*, *7(1),* 1-9.
Martinez, L., 2019. How Much Should We Trust the Dictator's GDP Growth Estimates? Journal of Political Economy 130(10), 2731–2769.
Menkhoff, L., and Miethe, J., 2019. Tax Evasion in New Disguise? Examining Tax Havens' International Bank Deposits. *Journal of Public Economics*, *176*, 53-78.
Michalopoulos, S., and Papaioannou, E., 2014. National Institutions and Sub-national Development in Africa. *Quarterly Journal of Economics*, *129(1),* 151-213.
Michalopoulos, S., and Papaioannou, E., 2018. Spatial Patterns of Development: A Meso Approach. *Annual Review of Economics*, *10(1),* 383-410.
Min, B., 2015. Power and the Vote: Elections and Electricity in the Developing World. *Cambridge University Press,* Cambridge, UK.
Miethe, J., 2020. The Elusive Banker: Using Hurricanes to Uncover (Non-)Activity in Offshore Financial Centers. *CESifo Working Paper* No. *8625*.
Noy, I., 2009. The Macroeconomic Consequences of Disasters. *Journal of Development Economics, 88(2),* 221-231.
OECD, 1998. Harmful Tax Competition: An Emerging Global Issue. *Organization for Economic Cooperation and Development, Paris*.
OECD, 2000. Towards Global Tax Cooperation: Progress in Identifying and Eliminating Harmful Tax Practices. *Organization for Economic Cooperation and Development, Paris*.
OECD, 2004. The OECD's Project on Harmful Tax Practices: The 2004 Progress Report. *Organization for Economic Cooperation and Development, Paris.*
OECD, 2011. The Era of Bank Secrecy is Over: The G20/OECD Process Is Delivering Results. *Organization for Economic Cooperation and Development, Paris.*
Pinkovskiy, M., and Sala-i Martin, X., 2014. Africa is on Time. *Journal of Economic Growth*, *19(3),* 311-338.
Pinkovskiy, M., and Sala-i Martin, X., 2016. Lights, Camera ... Income! Illuminating the National Accounts-Household Surveys Debate. *Quarterly Journal of Economics*, *131(2),* 579-631.
Pinkovskiy, M., 2017. Growth Discontinuities at Borders. *Journal of Economic Growth*, *22(2),* 145-192.
Raddatz, C., 2007. Are External Shocks Responsible for the Instability of Output in Low-Income Countries?. *Journal of Development Economics, 84(1),* 155-187.
Riedel, N., 2018. Quantifying International Tax Avoidance: A Review of the Academic Literature. *Review of Economics, 69(2),* 169-181.
Robertson, J., 2019. Global Financial Networks Confront Headwinds: China's Shifting Offshore Relationship with the British Virgin Islands. Pacific Review, *34(2),* 177-205.
Rose, A., and Spiegel, M., 2007. Offshore Financial Centres: Parasites or Symbionts?. *Economic Journal*, *117(523),* 1310-1335.
Shaxton, N., and Christensen, J., 2011. Time to Black-list the Tax Haven Whitewash. *Financial Times*, in: https://www.ft.com/content/0f687dee-5eea-11e0-a2d7-00144feab49a (Last accessed: 2021-09-17).
Skidmore, M., and Toya, H., 2002. Do Natural Disasters Promote Long-run Growth?. *Economic Inquiry, 40(4),* 664-687.
Slemrod, J., 2015. Tax Compliance and Enforcement: New Research and its Policy Implications. *Ross School of Business Paper 1302*.
Strobl, E., 2011. The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties. *Review of Economics and Statistics*, *93(2),* 575-589.

Sutton, P., and Costanza, R., 2002. Global Estimates of Market and Non-market Values Derived from Nighttime Satellite Imagery, Land Cover, and Ecosystem Service Valuation. *Ecological Economics*, *41(3),* 509-527.
Sutton, P., Elvidge, C., and Ghosh, T., 2007. Estimation of Gross Domestic Product at Sub-national Scales Using Nighttime Satellite Imagery. *International Journal of Ecological Economics & Statistics*, *8(S07),* 5-21.
Tørsløv, T., Wier, L., and Zucman, G., 2020. The Missing Profits of Nations. *NBER Working Paper 24701*.
Trinh, M., 2019. Statistical Misreporting from Below, as Seen from (Very High) Above. *MIT Political Science Department Research Paper No. 2019-22.*
Wallace, J., 2014. Juking the Stats? Authoritarian Information Problems in China. *British Journal of Political Science*, *46(1),* 11-29.
Young, A., 2012. The African Growth Miracle. *Journal of Political Economy*, *120(4),* 696-739.
Yu, B., Shi, K., Hu, Y., Huang, C., Chen, Z., and Wu, J., 2015. Poverty Evaluation Using NPP-VIIRS Nighttime Light Composite Data at the County Level in China. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *8(3),* 1217-1229.
Zucman, G., 2013. The Missing Wealth of Nations: Are Europe and the US Net Debtors or Net Creditors?. *Quarterly Journal Economics*, *128(3),* 1321-1364.
Zucman, G., 2014. Taxing Across Borders: Tracking Personal Wealth and Corporate Profits. *Journal of Economic Perspectives*, *28(4),* 121-148.