The elusive banker.

Using hurricanes to uncover (non-)activity

in offshore financial centers.

- *Job Market Paper* -

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September 15, 2018

Abstract: According to the governments and financial service providers in offshore financial centers (OFCs), the disproportionately high capital positions of small Caribbean and Pacific island jurisdictions result from a unique combination of human capital and tailored financial service products that attract international funds. Empirical economists on the other hand usually work under an assumption that not much of economic substance is happening there. Exploiting the natural experiment of hurricanes classified as natural disasters, this project compares the reaction of economic activity physically present on the island to impacts on financial activity. This is possible by constructing a dataset on monthly nightlight intensity from satellite data which is combined with several measures of financial activity and exposure. Nightlights drop by around 20-30% after a storm with recovery taking around half a year. Financial activity in OFCs, however, shows no reaction whatsoever. Investor responses are also absent. Validating the identification strategy, all these reactions are visible in the 'real world' of non-OFC islands. The only variable where some effects is documented for OFCs are daily company incorporations taken from leaked company registries. In more descriptive evidence, the project also documents the absence of a direct link between local economic activity and foreign bank positions in OFCs. These findings suggest that the financial activities leading to the large international capital positions of OFCs take place elsewhere and are decoupled from local economic activity on the island.

JEL classification: C82, H26

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1 Introduction

The disproportionately high capital positions in offshore financial centers (OFCs) have received increasing scrutiny over the last years. OFCs are accused of using their secrecy, low to zero tax rates, and lax regulation to attract capital merely by providing opportunities for regulatory arbitrage. On the other hand, companies and funds active on OFCs argue that these play a vital role in their international investment strategies, providing a set of unique skills and services supporting their activities. Such services include wealth management services, fund incorporation and management, single point of entry solutions, and the setting up of sophisticated corporate structures involving multiple entities and jurisdictions. Fund managers and even official government aid institutions[1] cite the services and skills in an OFC such as Mauritius as a reason for their use of OFCs to invest in low income jurisdictions that lack skills for such structures.

The empirical economic literature on the other hand usually operates under an assumption that few if any economic activities are taking place on OFCs. Instead, ownership structure are assumed to show passive deposits or assignment of ownership (Garcia-Bernardo et al., 2017; Zucman, 2013). With the data sources employed here, this assumption becomes testable against the assertions mentioned above. Two hypotheses emerge: First, such activity should react to exogenous shocks that affect the OFC. Here, re-occuring natural disasters in the form of hurricanes are used as such a shock. Second, even without exploiting natural experiments, some connection between financial and local economic activity should be present if the former physically takes place on the OFC.

OFCs are characterized by low regulatory requirements, especially in areas of banking regulation and finance, high secrecy rules, and low to zero tax rates. They have other things in common that point towards an advantage in providing financial services: they are economically open, provide relatively sophisticated communications infrastructure and perform well on governance indicators measuring political and legal stability as well as corruption (Dharmapala, 2008; Dharmapala and Hines Jr, 2009). Banks and non-bank Financial Institutions (NBFIs) themselves emphasize the professional banking services and the quality of legal, accounting, and trust and management services that OFCs provide.

However, surprisingly little reliable econometric evidence is available concerning the activities carried out inside OFCs. Most recent empirical research focuses on indirect identification strategies. Johannesen and Zucman (2014) show reactions of bank deposits to information exchange upon request agreements aimed at detecting tax evaders inside the OFC with Hanlon et al. (2015) providing similar results for US portfolio investment inflows. Work on the EU

[1] Some of Germany's official development aid is structured via Mauritius, the 2015 report of the German Investment and Development Society (DEG) shows nine fund participations in Mauritius: https://www.deginvest.de/DEG-Dokumente/Download-Center/Jahresabschlussbericht_2015_D.pdf.

savings directive also confirms such tax evasion effects (Johannesen, 2014). Another strand of the literature is targeted at evaluating the profit shifting strategies of multi-nationally active firms by showing for example firms shifting subsidiaries or banks moving trading activity into OFCs to avoid regulation or taxation (Caruana-Galizia and Caruana-Galizia, 2016; Langenmayr and Reiter, 2017). Again, indirect strategies in reactions to certain policy changes dominate (Dharmapala et al., 2011). The few aggregate estimates that exist point to large positions with around 8% or 4.5 trillion of private wealth stashed offshore (Zucman, 2013). Tørsløv et al. (2018) estimate artificial profit shifting by multinational companies to be in the magnitude of 600 billion in 2015 alone. If anything, financial integration with OFCs is increasing (Milesi-Ferretti and Lane, 2017).

Crucially, while many of these activities profit from an accommodative regulatory environment, they also rely on financial service providers setting up the tax avoidance scheme, incorporating the shell company or managing the offshore trust. On paper, such financial services inflate macroeconomic statistics. For example, with $85,700, Bermuda is the richest country on the planet in GDP per capita terms. It is, however, an open question how much of this activity actually takes place in OFCs and to what extent these jurisdictions are used as fig leaves that on paper feature these large positions but in reality do not contribute the financial services. While this presumption might be shared by many, to my knowledge the only available evidence that activity on OFCs is artificial is provided in Langenmayr and Reiter (2017). For a sample of German banks, they provide tentative evidence that banks themselves use OFC's for their own profit shifting strategies by shifting trading activity but not employees to OFCs. Whether such behavior extends to services they provide to their customers is an entirely open question.

Studies into the nature of OFCs are plagued by data limitations. In order make some progress here, I construct and employ several several new data-sources that shed light on both real economic activity and financial activity on OFCs. First, I construct a comprehensive monthly nightlight dataset based on satellite images for both entire jurisdictions as well as their subnational regions. This measure is used as a proxy for local economic activity that physically takes place on the island in question. Second, I use bilateral bank claims reported by a large number of OECD economies against the small islands jurisdictions under study here. These mirror claims measure financial exposure and bank investment from the rest of the world. Third, equity price data on banks and non-bank Financial Institutions (NBFIs) domiciled in OFCs are used to check for investor responses. These measures are also constructed for non-OFCs. However, financial data on OFCs and non-OFCs is strictly separated in this study. Developments and reactions in non-OFCs are merely investigated as a 'real-world' test of the identification strategy.

To evaluate what kind of activity takes place on OFCs, the natural experiment of re-occurring hurricanes in the Caribbean and Typhoons in the Pacific (both subsumed under 'hurricanes' henceforth) is investigated as a source of exogenous variation. Based on the commonly used list of 'treasure islands' provided by Hines (2010) or Gravelle (2015), 18 such offshore finance islands as are located in the 'hurricane alley' of the Caribbeans and the Atlantic Ocean. Another 10 are situated in the Pacific and regularly hit by Typhoons. Both regions also include numerous islands that do not carry out offshore finance activities.

In spite of several 'crackdowns on tax havens', many of these OFC islands continue to maintain low to no reporting requirements and regulations for financial institutions. Around 50% of funds booked via OFCs are booked through islands hit by hurricanes which allows the analysis of a relevant fraction of the offshore world. Disaster type hurricanes in these regions lead to extended power outages, disabled infrastructure, evacuations, flooding, and direct casualties. Indeed, local economic activity in OFCs as measured in the monthly nightlight dataset constructed here drops by around 20-30% after a hurricane hits. Recovery takes around six months, an effect in line with the literature on natural disasters (Mohan and Strobl, 2017a; Strobl, 2011, 2012). These results hold both on the national and the sub-national level.

However, effects of these natural disasters on financial activity in OFCs are entirely insignificant both statistically and economically. Investor responses are also absent. This suggests, that financial activity continues unabated while local economic activity drops by a third on average. This begs the question who carries out these activities and if whoever it may be is actually on the Island or rather in the headquarter in London or New York. To test the identification strategy, the 'real world' baseline in the form of non-OFC islands is investigated and here, loans and assets held by international banks against the island, are reduced by 10-30% and investors experience strong negative abnormal returns after hurricane impacts.

There is one measure however, in which a small reaction on hurricane impacts is visible in offshore financial centers. One of the most cited activities taking place in OFC's is the incorporation of shell companies. I construct a dataset on daily company incorporations - including shell companies - from several OFC corporate registries leaked in the Paradise papers. While data here is limited to a few OFCs, a significant drop is visible on hurricane impact. This suggests that there is a differentiated effect across service provision in OFCs and that some activity does take place there, even if it is just a stamping incorporation documents.

A second set of results aims at comparing the relation between financial positions and local economic activity in the raw data. A positive correlation between the two is readily observable for non-OFCs both in levels and in within-jurisdiction changes. For OFC's, it is absent. Thus, even descriptive evidence documents a missing link between local economic and financial activity on OFCs in the new data sources employed here.

This project contributes to the literature in three important ways: First, research on offshore financial centers is plagued by the absence of reliable data. Here, this situation is improved upon by (a) employing monthly satellite data on nightlight intensity as a measure of real economic activity available for any island no matter how small and (b) establishing what kind of financial activities takes place on the island using several data sources: BIS mirror data, equity prices on banks and NBFIs domiciled there, and leaked incorporation data. Second, these data sources allow an investigation of contested claims such as a disconnect between finance and local economic activity. Little to no previous empirical evidence is available to verify such claims. Third, the project employs the natural experiment of re-occuring hurricanes as a source of exogenous variation in local conditions. This setup allows us to differentiate two factors in the attractiveness of offshore financial centers: Their accommodative regulatory environment, which should not react to hurricanes, and their contribution to efficient banking by potentially being home to some of the most advanced financial service providers and internationally active banks and their subsidiaries.

The paper proceeds as follows. Section 2 introduces the identification strategy based on hurricane impacts in detail. Section 3 outlines the data sources used: geo-spatial data on nightlight intensity, hurricane data and data measuring financial service activity and integration. Section 4 provides results on hurricane impacts, comparing the responses of local economic activity and international investment positions. In section 5, extended results on the direct relationship between these variables are provided and section 6 concludes.

2 Identification: The natural experiment of re-occurring hurricanes

Empirical research on offshore finance faces two non trivial problems: First, macroeconomic data on small island economies are notoriously unreliable if even available and, as the example of GDP per capita in Bermuda shows, potentially inflated. Second, the researcher has to identify reactions of activities that are oftentimes shrouded in secrecy or at least not officially recorded. The data problem is addressed in the data section. This section focuses on the identification of offshore finance activities in the second part of the analysis: differentiated reactions of the real economy and financial positions and service provision to an exogenous shock.

Usually, identification in research on offshore finance is achieved by exploiting regulatory changes that change the incentive structure of agents who exploit certain regulations (see Slemrod, 2015; Zucman, 2014, for overviews). In this project, I propose an different identification strategy based on the natural experiment of re-occurring storms as a source of exogenous variation.

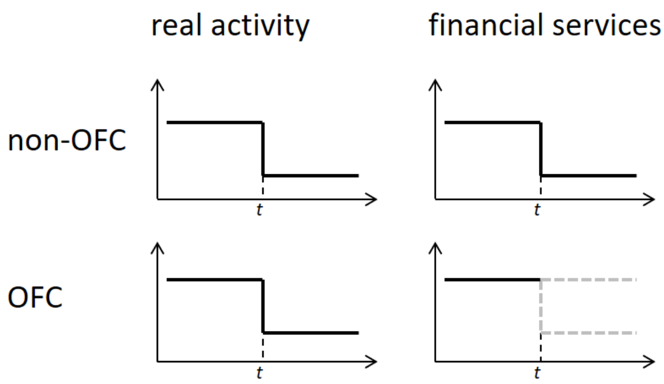
The Caribbean sample under study here is called 'hurricane alley' due to the re-occurring tropical storms that form over the gulf stream. Islands in the Pacific are more spread out but still prone to regular typhoons. Only disaster-type hurricanes are used here that reach devastating destructive potential. Hurricane Irma in autumn 2017, for example, directly affected 1.2 million people with wind speeds of up to 295 kilometers per hour, caused at least 130 deaths, lead to damages of 50 billion USD in the United States alone, and cut electricity for several million inhabitants on Caribbean Islands and Florida (US Office for Coastal Management[2]). The hurricane affected seven OFC territories (Antigua and Barbuda, St. Maarten (Dutch Part), St. Lucia, Barbados, St. Kitts and Nevis, Anguilla, and the British and US Virgin Islands) and six non-OFC islands (Puerto Rico, Saint Martin (French Part), US Virgin Islands, Guadeloupe, Haiti, Cuba) as well as parts of the US. Local impacts were be substantial, 90% of all buildings on Barbuda, for example, were destroyed.

Such storms affect local economic activity. Economic impact of hurricanes established in the literature range from 0.45% to 1.5% lower GDP growth in a given year (Bertinelli and Strobl, 2013; Strobl, 2011, 2012). Effects usually last several months before the drop is made up for. Two existing studies showing the impact of nightlights on single islands show an effect lasting up to 15 months in the Dominican Republic (Ishizawa et al., 2017) and around 7 months for cyclone Pam hitting the pacific island of Vanuatu (Mohan and Strobl, 2017b). I use these reactions of real economic activity to test if hurricanes actually affect OFCs to a significant extent. Additionally, I compare the impact in non-OFCs to provide a 'real world' test.

Figure 1 summarizes the resulting hypothesis. Assume a hurricane hits an OFC in time t. The

[2] Last accessed 27th of February, 2018, at: https://coast.noaa.gov/states/fast-facts/hurricane-costs.html

Figure 1: **Schematic reactions to hurricane impacts**



Notes: Hypothetical reactions to hurricane impact at time t on the horizontal axis for offshore financial centers (OFCs) and non-OFCs.

first column of figure 1 indicates the potential drop in real economic activity that I expect. The identifying assumption now is, that banks and non-bank financial institutions (NBFIs) cannot completely isolate themselves from this shock. The magnitude of the effect can differ compared to non-OFCs, but the presence or absence of financial service provision as an activity physically carried out in OFCs would be mirrored by the reaction in column 2 row 2 of figure 1. If it is indeed the skilled banker providing the service that leads to the large capital positions of OFCs, her activity should suffer from power outages, infrastructure breakdowns and the physical destruction of her office. If hurricanes decrease real economic activity on OFCs and leave financial data unaffected, however, this is evidence that the financial service is carried out elsewhere and merely booked through the OFC. In this case, the only 'service' that the OFC provides is an opportunity for regulatory arbitrage or legal environments and no contribution to the efficiency of financial service provision can be attributed to OFCs. The offshore banker remains elusive.

Non-OFCs are investigated as an additional test of this identification strategy: they provide a 'real world' comparison here. These are separate samples so no difference-in-difference assumptions are maintained between OFCs and non-OFCs. Still, if no reaction of hurricanes in financial activity on non-OFC were visible, this would cast serious doubt on the identification strategy. In effect, testing non-OFCs relaxes the identifying assumption to: Banks and NBFIs cannot insulate themselves to hurricanes completely *when their counterparts on non-OFCs cannot.*

However, it is necessary to establish that hurricanes hit OFCs and cause significant damage. Only then would we expect reactions in financial service provision. Investigating these reactions is therefore done in two steps: First, the impact of hurricanes on real economic activity is determined. Second, the reaction of financial variables is tested. Finally and disregarding hurricanes, a direct connection between local and financial activity is investigated. The following section outlines the data necessary to carry out these exercises.

3 Filling the data gap in offshore finance

The strength of the identification strategy outlined above is that there are a large number of OFC as well as non-OFCs in the Caribbean[3] and in the Pacific[4] that are both hit regularly by hurricanes. This differentiation is based on common tax haven lists employed in the literature and, for both regions, quite consistent both over time and over different studies (for commonly used lists see Gravelle, 2015; Hines, 2010; Hines Jr and Rice, 1994)[5]. Most of these countries are small island economies with little to no available macroeconomic data.

To fill this gap, I propose the use of several data sources with large to complete coverage. First, satellite data on nightlight intensity is introduced and used in combination with geo-spatial data on geographic boundaries of the jurisdictions in question to construct a monthly dataset of nightlight intensity from 2012:4 to 2017:12. Second, BIS data on bank claims reported by all reporting non-OFCs, including large OECD countries, against both bank and non-bank counterparties is introduced. These positions are reported against a large number of jurisdictions, including the majority of countries under study here. Fourth, the leaked corporate registries of Aruba, the Cook Islands, the Bahamas, Barbados, Nevis and Samoa are taken from the Panama and paradise paper leaks by the international consortium of investigative journalists. These registries include incorporation dates and are used to construct daily time series of incorporations on these islands. Finally, the section shortly introduces additional data sources on hurricane data.

Crucially, none of these four data sources relies on information deliberately reported by the OFCs themselves which alleviates concerns of mis-reporting or data quality.

3.1 A monthly nightlight dataset including small island jurisdictions

Satellite data has been in frequent use amongst development economists trying to measure economic conditions in remote areas or countries with unreliable national accounts. Henderson et al. (2012) provide the seminal contribution relating nightlight data to economic growth and a

[3]Caribbean OFCs in the sample: Aruba, Anguilla, Antigua & Barbuda, the Bahamas, Belize, Bermuda, Costa Rica, Curaçao, Cayman Islands, Dominica, Grenada, St. Kitts & Nevis, St. Lucia, Montserrat, Panama, Turks & Caicos Islands, Trinidad & Tobago, St. Vincent & Grenadines, British Virgin Islands, U.S. Virgin Islands. Caribbean non-OFCs: Dominican Republic, Ecuador, Guadeloupe, Guatemala, Guyana, Honduras, Haiti, Jamaica, Martinique, Nicaragua, Puerto Rico and El Salvador.

[4]Pacific OFCs: Marshall Islands, Singapore, Hong Kong, Macau, Malaysia, Vanuatu, Nauru, Mauritius, and the Seychelles. Pacific non-OFC islands and coastal countries: Sri Lanka, Micronesia, Guam, Northern Mariana Islands, Palau, Brunei, Christmas Island, Cocos (Keeling) Islands, Fiji, Kiribati, Tuvalu, Solomon Islands, South Georgia & South Sandwich Islands, Reunion, Madagascar, Mayotte, and Comoros.

[5]The difference in these lists relevant to the Caribbean is the classification of Costa Rica which is not included as an OFC in older lists. However, since the main sample used here starts in 2012, it is included in this project.

useful summary of applications of satellite data in the empirical economics literature is available in Donaldson and Storeygard (2016). Most sources in the literature relating storms to nightlight as well as most studies in development economics are based on an older yearly data source of DMSP satellites (Bertinelli and Strobl, 2013).

This satellite Program has been followed up by Nasa and the NOAA National Geophysics Data Center by the Visible Infrared Imaging Radiometer Suite (VIIRS) that provides several improvements useful for the analysis at hand. First, it is much more precise with a resolution of around 750 meters at the equator, lower light detection limits, and several technical improvements for data comparability as scans move away from the equator (see Elvidge et al., 2017, for further details). The new satellite has a nightly overpass time at 1:30 am and has no light saturation point that limited distinctions of very light areas in the older data (Mohan and Strobl, 2017a). The resulting images are aggregated into monthly composites and corrected for stray light, lightning, cloud cover and other outliers (Elvidge et al., 2017).

These large monthly nightlight maps are available from the Earth Observation Group, NOAA National Geophysical Data Center[6] and are combined geospatial data on national and regional boundaries. These spatial polygons are available for all jurisdiction relevant here via the Global Administrative Areas dataset [7]. Figures 2 and 3 plot a part of the Caribbean using these data sources at different points in time. Visible in shaded areas are the British and the US Virgin Islands. The spatial polygons of the country boundaries, plotted in grey, have only been added for the British Virgin Islands here. Hurricanes Irma and Maria hit the British Virgin Islands in September 2017 and the drop in nightlight intensity of this one hurricane is already visible by visual inspection.

Within the country polygon, it is now possible to calculate nightlight statistics such as the mean, median or standard deviations of the nightlight intensity of each pixel in that jurisdiction and that month. By performing such calculations for each jurisdiction and going though all available monthly nightlight maps, a monthly panel dataset is created running from April 2012 until December 2017 for every jurisdiction in the sample. These data are the basis for calculating the real impact of hurricanes, relying on the extensive literature linking nightlights to economic activity. The advantage of this dataset is that is completely free of data gaps and of a relatively high frequency. Data on Montserrat, a British Overseas Territory with only around five thousand inhabitants and little usable data from other sources, are just as readily available as data on Jamaica with 3 million inhabitants. Radiance of nightlight is measured in units of $Wcm^{-2}sr^{-1}$, or watt per steridian per square centimeter. For usability, these radiance values have been multiplied by $1E9$ by the NOAA National Geophysical Data Center. They are used in the resulting unit here which leads to a continuous scale leading to a maximum of around 30

[6]Last accessed on the 12th of June 2018 at: https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html
[7]Last accessed on the 12th of June 2018 at http://www.gadm.org/country

Figure 2: **Nightlights in the British Virgin Islands pre Irma & Maria**

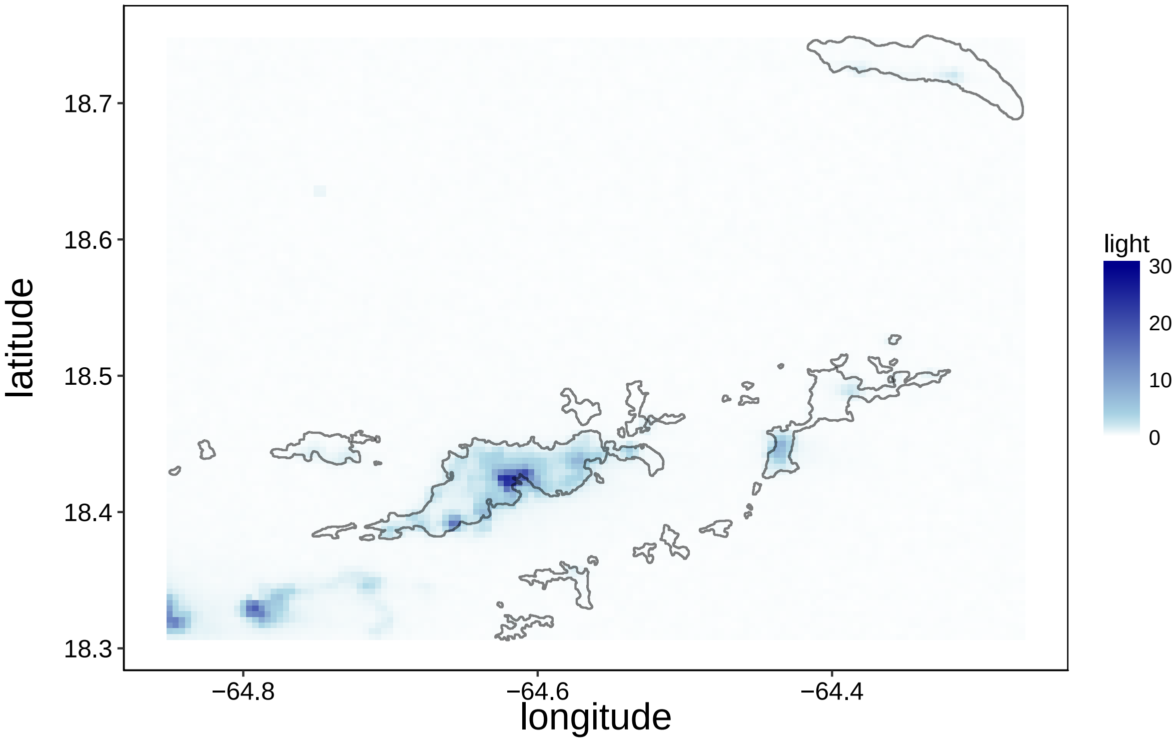
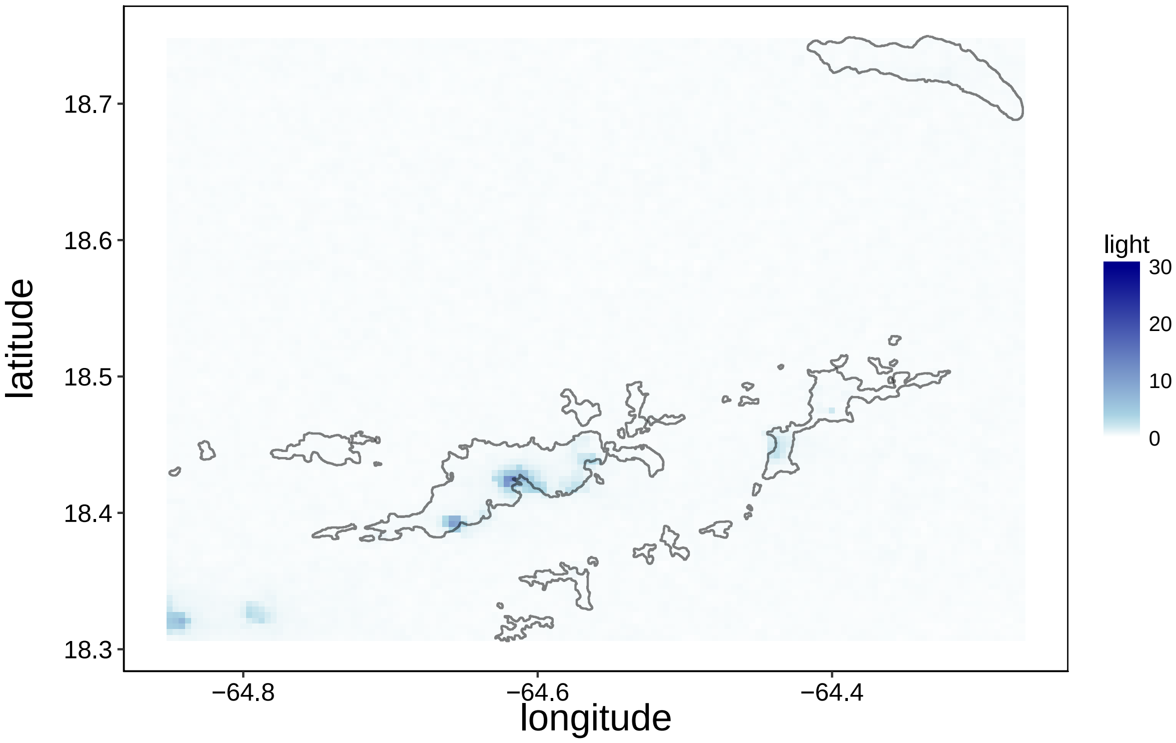


Figure 3: **Nightlights in the British Virgin Islands post Irma & Maria**



Notes: Shows nightlight intensity for the British Virgin Islands (center) and the US Virgin islands (south-west) and the country polygon (in grey borders) for the British Virgin Islands only. Figure 2 shows nightlight intensity in Aguust 2017, before hurricanes Irma and Maria hit the islands. Figure 3 shows the same area in October 2017 after these hurricanes. The mean of nightlight intensity inside a country polygon forms the basis of the monthly nightlight dataset used as a measure of real economic activity. Radiance of nightlight is measured in units of $Wcm^{-2}sr^{-1}$, or watt per steridian per square centimeter multiplied by $1E9$.

for most jurisdictions in the sample.

The resulting monthly nightlight dataset and the associated R-code building it is available on request from the author, however, a number of caveats are important to point out. First, these data do not control for rural versus urban agglomerations within regions. Goldblatt et al. (2017) provide some a proof of concept how this could be achieved in the future using high resolution imagery taken from the Landsat satellite but it is not necessary here. The level of the data, such as the average light intensity, can be influenced by parts of the geographical are that are not illuminated such as small remote islands associated with a larger island. I run robustness checks based on regional data which confirm the results indicating that for the current project, the granularity applied suffices. A second caveat concerns the blooming effect: As figures 2 and 3 show significant portion of the light 'blooms' out over the sea: this is not captured in this data as the geographical confines of the jurisdiction in question is used to process the nightlight data. Again, this is not relevant for the analysis presented here as I do not compare the level of nightlight intensity but changes and developments over time.

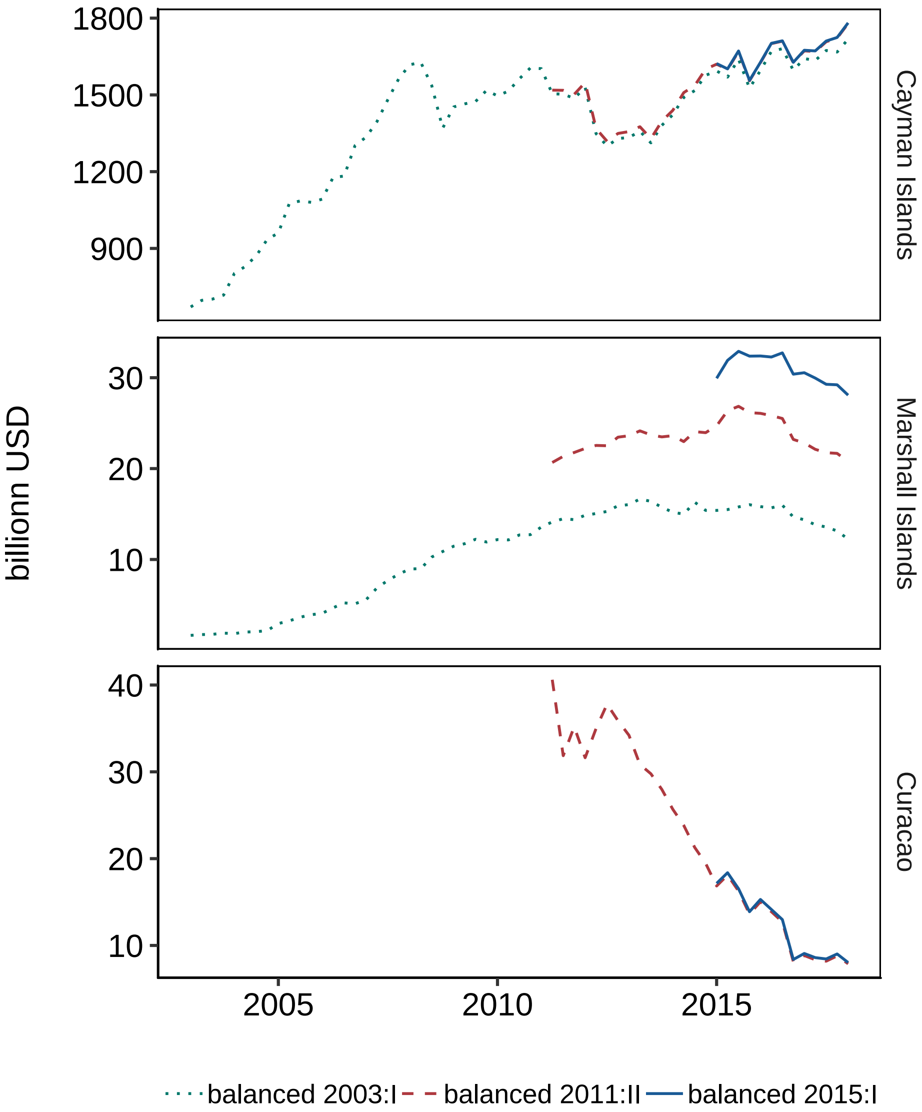
3.2 Financial data

The data availability problem in offshore finance extends to data on financial positions and service provision. In order to alleviate this problem, two data sources are introduced here: Mirror data of BIS claims reported by other countries against these small islands, and daily company incorporation series. In order to be meaningful for the identification strategy outlined above, financial data has to satisfy three conditions. (I) The activity needs to take place in an OFC, ruling out most industry or agricultural activities. (II) The activity needs to take place in a non-OFC ruling out pure profit shifting strategies. (III) The activity needs to react to hurricane impacts meaning that their needs to be a physical manifestation of these activities, at least in theory.

3.2.1 Mirror data of bank claims

In its Locational Banking Statistics (LBS), the Bank for International Settlements provides bilateral quarterly time series on banks' international claims and liabilities on an immediate counterparty basis. So far, only bank deposits, a subsets of the liabilities reported in these data, have been analyzed in the tax evasion literature with claims relegated to robustness checks (Johannesen, 2014; Johannesen and Zucman, 2014; Menkhoff and Miethe, 2018). Here instead, I propose the use of mirror data on bank claims reported by non-OFCs. The BIS provides loans to foreign counterparties as a subcategory of international bank claims.[8]

Figure 4: **Mirror claims for selected countries**



Notes: Shows three versions of balancing the countrypairs from which mirror claims are constructed: one starting with the sample available in 2003:I (green, dotted), one starting in 2011:II (red, dashed), and one starting in 2015:I (blue, solid). The vertical axis reports the total claims reported against the respective country by all reporting countries combined.

While coverage is not complete, the BIS dataset includes most relevant OECD countries including the United States and the United Kingdom. A total of 46 national central banks report the international claims and liabilities of banks under their supervision to BIS on a bilateral basis and in quarterly frequency. While only 5 OFCs of the Caribbean sample here report such data, mirror claims can be constructed against a total of 19[9] island and coastal OFCs and 18

[8] The BIS also provides loans against non-banks only as a subcategory of these data but since this category would include non-bank financial institutions such as offshore financial service providers, this differentiation is not used here. The data used thus include both loans to banks and to non-bank financial institutions.

[9] These are: Aruba, Bahamas, Belize, Bermuda, Barbados, Costa Rica, Curacao, Cayman Islands, Dominica, St. Lucia, Marshall Islands, Panama, Seychelles, Turks & Caicos Islands, Tonga, Trinidad & Tobago, St.

island or coastal non-ofcs[10] both either in the Caribbean or in the Pacific and all exposed to hurricanes. On top of the nightlight data introduced above, these mirror claims are a second step in filling the data gap in offshore finance.

Mirror claims of a country in the sample are thus calculated as follows:

$$Mirrorclaims_{it} = \sum_{j=1}^{J} claims_{jit} \tag{1}$$

Where country i can either be an OFC or a non-OFC and claims are summed for the entire population of non-OFCs, $j = 1, ..., J$, that report bank claims data to the BIS.

Reports by different countries and against different counterparties start at different points in time. A sample balanced in the second quarter of 2011, when satellite data becomes available as well, shows almost complete coverage and no systematic bias. Figure 4 shows mirror claims against three countries to highlight the main results in three different balancing schemes. The green dotted line show a sample balanced in 2003:I to check if reporting increased substantially before 2011. The red dashed line shows the sample for which nightlight data is also available and which is used here. The solid blue line shows a sample balanced in 2015:I to show how much is lost by this choice.

The financially largest OFC in the sample, the Cayman Islands (top panel), exhibits increasing claims over time as do most OFCs. The largest OECD countries already report claims against this country in 2003 meaning that the three series don't deviate much and both the level and the dynamics are well captured by the series starting in 2011:II. The Marshall Islands have received much less scrutiny and coverage is still increasing as the level shift between the three series shows. Still, the time dynamics especially of the 2015 series seem well captured in the 2011 series used. Some OFCs, such as Curacao (bottom panel) exhibit decreasing deposits over time. Since Curacao only split with Sint Maarten and Bonaire (formerly the Netherlands Antilles) in 2010, no 2003 series can be compared here but the 2011 and the 2015 series are closely aligned.

Thus, while countrypairs for which data becomes available only after the second quarter of 2011 are lost as a result of this balancing choice, figure 4 does suggest that this loss is tolerable. Crucially, these mirror claims can therefore also be constructed for islands as small as the Turks and Caicos Islands with 52,570 inhabitants but a total of 507 million USD of mirror claims reported against it in 2018 Q1, 206 million of which reported by non-OFCs in the sample

Vincent & Grenadines", "Vanuatu, Samoa

[10]These are: Cuba, Dominican Republic, Fiji, Guatemala, Guyana, Honduras, Haiti, Jamaica, Kiribati, Sri Lanka, New Caledonia, Nicaragua, Papua New Guinea, French Polynesia, Solomon Islands, El Salvador, Tuvalu, Wallis & Futuna

balanced in 2011. Appendix Appendix A.1, provides more information on the development of coverage over time.

3.2.2 Data on equity prices

In order to test responses of international investors directly, I construct a dataset of 395 equity price series taken from Bloomberg. These equities are traded on different stock exchanges but only data on companies domiciled in one of the sample islands is used here. These series are limited to the sample sample length, starting on the first of April 2011 and ending on the last day of 2017. Data is available on banks as well as non-bank financial institutions such as holding companies, insurance firms, credit companies and other financial service firms. The series are used in a straightforward event study in the spirit of Kothari and Warner (2007). The associated transformations are introduced together with the results further below.

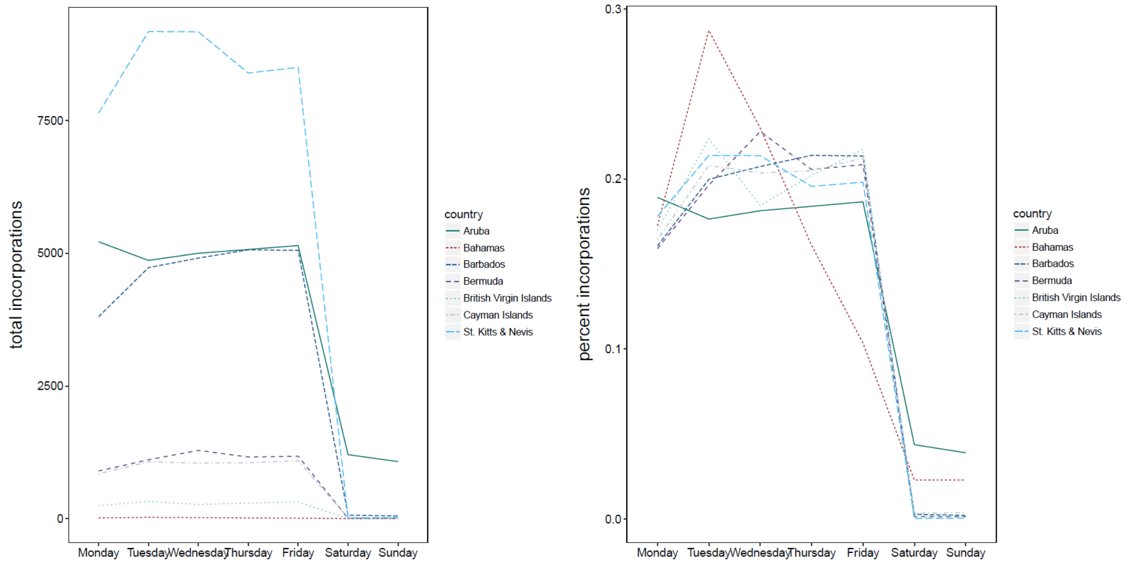
3.2.3 Company registration data

Corporate registries of OFCs are generally not publicly available. However, in February 2018, the international consortium of investigative journalists (ICIJ) published the leaked corporate registries of Aruba, the Cook Islands, Bahamas, Barbados, Malta[11], Nevis and Samoa on top data on company registrations carried out by the offshore law firm Appleby that received more media attention but is less comprehensive. While such incorporations can be prepared elsewhere, as is the case for Appleby, there needs to be at least a formal director signing the document and a local authority accepting the incorporation if the administrative arm of a country functions. There have been scandals in the past of names of deceased directors appearing on such applications which is why it is still plausible that this common route is circumvented in practice.

Without Appleby, the leaked registries have data on 265.150 unique company registrations including their incorporation dates. For the five OFCs in the sample where the complete company register was leaked, these data are aggregated into time series counting the number of incorporations per day. These time series can then directly be compared around hurricane dates. As figure 5 shows, this data survives a sanity check: incorporations do take place during the work week and not on weekends, an indication that they should reflect actual activity.

[11] Malta is not included in the current project as not in a hurricane area.

Figure 5: **Incorporations over the week**



Notes: Shows total incorporations (panel 1) and percent incorporations (panel 2) by weekday (corporate registers and Appleby registrations combined) for selected OFCs in the Caribbean.

3.3 Data on hurricanes

The literature focused on establishing precise growth declines due to hurricanes (see for example Strobl, 2011, 2012) goes into great detail when it comes to precise geo-spatial impact estimations of hurricanes. In the present project, hurricane impacts have to be analyzed at the national level because financial data is only meaningfully analyzed nationally given existing data. Regional data is used as a robustness check and confirms the results. The BIS data is based on nationality and corporate registers are national. National data on hurricanes is taken from the EM-DAT[12] disaster database that collects the exact timing of hurricanes in the Caribbean including statistics on the number of population affected as well as locations affected. This dataset includes hurricane Irma, the most devastating hurricane hitting the Caribbean since VIIRS satellite data is available. Since hurricanes can be dated precisely, this data can be used at all frequencies employed here: monthly together with data on nightlight intensity, daily together with incorporation data, and quarterly to analyze BIS bank claim data.

[12]The Emergency Events Database - Universit catholique de Louvain (UCL) - CRED, D. Guha-Sapir - www.emdat.be, Brussels, Belgium

Table 1: **Major Caribbean hurricanes since 2012**

Name	start - end dates	OFC hits	non-OFC hits
Isaac	21.08.2012 - 03.09.2012	no	yes
Sandy	22.10.2012 - 29.10.2012	yes	yes
Erika	24.08.2015 - 28.08.2015	yes	yes
Joaquin	28.09.2015 - 15.10.2015	yes	no
Matthew	28.09.2016 - 10.10.2016	yes	yes
Irma	30.08.2017 - 14.09.2017	yes	yes
Maria	16.09.2017 - 03.10.2017	yes	yes

Notes: Shows hurricanes affecting the Caribbean since 2012 as well as their start and end dates in columns 1 & 2. Columns 3 & 4 indicate weather only OFCs, only non-OFCs or both have been hit by the specific hurricane.

To provide an idea of this shock variable, table 1 shows the Caribbean hurricanes in the sample during the time for which monthly nightlight data is constructed. As can be seen, two particularly strong hurricanes fall into the sample time: Hurricanes Irma and Maria (indistinguishable in a monthly dataset as both took place in September 2017) and hurricane Sandy in 2012. Most hurricanes hit both OFCs and non-OFCs making it possible to compare impacts of the same storm on different islands and different variables.

Table 2 summarizes the data on island economies of the data-sources introduced so far. Several facts are noteworthy. First, the average OFC indeed is quite small. The Cayman Islands and Bermuda for example only have 60 and 70 thousand inhabitants respectively but large mirror claims. It is also apparent that GDP per capita and poverty rates, retrieved from the CIA world fact book where available, vary substantially across the sample. The nightlight mean and standard deviations are available for all OFCs here as pointed out above and can therefore be used to evaluate hurricane impacts the frequency of which also varies across countries.

Table 2: **Descriptive statistics on Caribbean & Pacific island economies**

country	population	GDP p.C.	poverty in %	mirror claims 2018q1	mean(light)	sd(light)	hurricanes since 2011q2	OFC
Aruba	115,120	25,300	–	0.049	5.440	1.138	0	1
Anguilla	17,087	12,200	23	–	3.131	0.509	1	1
Antigua & Barbuda	94,731	26,300	–	–	2.497	0.158	1	1
Bahamas	329,988	25,100	9	105.200	0.548	0.085	6	1
Bermuda	70,864	85,700	11	63.570	6.704	0.644	0	1
Curacao	149,648	15,000	25	22.060	6.193	0.930	0	1
Cayman Islands	58,441	43,800	–	1,547.000	4.862	0.473	0	1
Dominica	73,897	12,000	29	0.034	0.325	0.085	3	1
Dominican Republic	10,734,247	17,000	31	2.511	0.799	0.134	7	0
Fiji	920,938	9,900	31	0.368	0.104	0.093	3	0
Guadeloupe	397,990	–	–	–	2.576	0.161	1	0
Haiti	10,646,714	1,800	59	0.176	0.158	0.083	7	0
Jamaica	2,990,561	9,200	17	0.914	1.230	0.107	2	0
St. Kitts & Nevis	52,715	26,800	–	–	2.185	0.192	1	1
St. Lucia	164,994	26,800	–	0.035	1.854	0.116	2	1
Montserrat	5,292	8,500	–	–	0.248	0.091	0	1
Martinique	380,877	27,305	17	–	3.757	0.197	2	0
Nauru	11,359	12,200	–	0.001	3.338	1.057	0	1
Papua New Guinea	6,909,701	3,700	37	0.661	0.046	0.074	2	0
Puerto Rico	3,351,827	37,900	–	–	4.602	0.622	4	0
Solomon Islands	647,581	2,200	–	0.050	0.016	0.078	2	0
Turks & Caicos Islands	52,570	29,100	–	0.199	0.685	0.093	1	1
Trinidad & Tobago	1,218,208	31,200	20	1.546	6.200	0.290	0	1
Tuvalu	11,052	3,700	26	–	0.102	0.093	1	0
St. Vincent & Grenadines	102,089	11,600	–	0.530	0.733	0.105	2	1
British Virgin Islands	35,015	42,300	–	–	1.551	0.254	1	1
U.S. Virgin Islands	107,268	36,100	29	–	5.797	0.971	1	1

Notes: Shows data on island economies in the Caribbean and in the pacific. Population, GDP per capita, and poverty rates (where available) are taken from the CIA world factbooks most recent estimates (Jul. 2017 where available). Column 4 shows the sum of international claims (in billion USD) reported on the OFC by all non-OFCs that provide data to the BIS locational banking statistics in 2011q2 or earlier. Columns 5 and 6 show means and standard deviations of nightlight intensity over the sample period (2012:4 - 2017:12). Column 7 shows the number of hurricanes after 2011q2 and column 8 finally indicates if the jurisdiction is classified as an OFC or not.

4 Empirical Results

This section proceeds in two steps. First, results of the impact of hurricanes on real economic activity measured by nightlight intensity are analyzed. These results are then compared to reactions of foreign bank and market participants invested in banks and non-bank financial institutions (NBFIs) on OFCs. Three types of results are provided in this second step: Results on mirrorclaims capturing foreign bank lending, investor responses in stock return data on banks and NBFI's domiciled on OFCs, and finally some indicative evidence on local incorporations. In both steps I also provide tests in the non-OFC sample to test the identification strategy in the 'real world'.

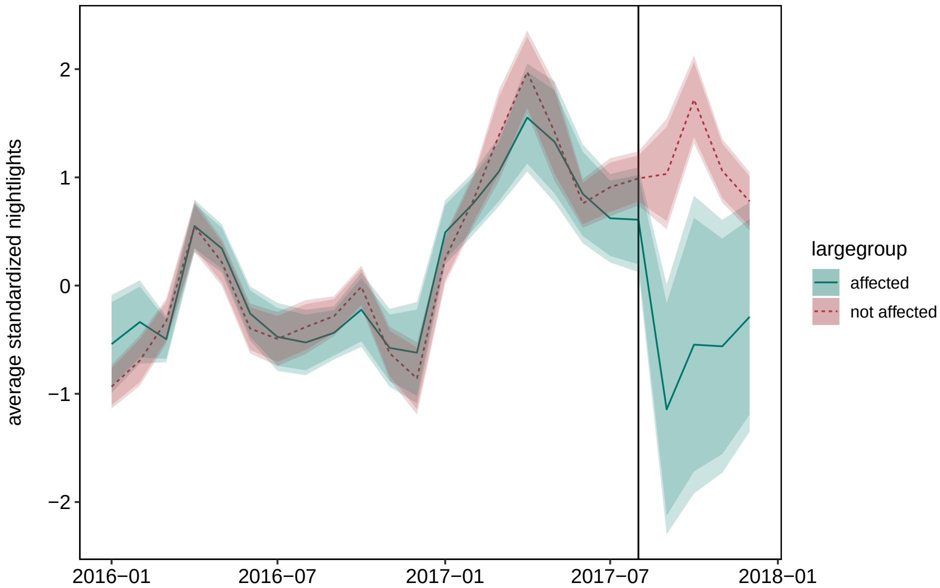
4.1 Nightlights and hurricanes in OFCs and non-OFCs

Adding to the anecdotal evidence on hurricane impact, such as 95% of houses on Sint Maarten uninhabitable after hurricane Irma, the impact of hurricanes on nightlight intensity are a modest contribution in their own right. No panel results on the Caribbean using VIIRS data exists to date. Available studies focus on the effects on GDP of hurricanes hitting South America and the Caribbean (Strobl, 2011) as well as US county per capita income (Strobl, 2011). Hurricane impacts on nightlights have been analyzed in the Caribbeans using the older yearly DSMP data mentioned above (Bertinelli and Strobl, 2013) with only one study employing VIIRS data to analyze the impact of cyclone Pam in the Pacific Ocean (Mohan and Strobl, 2017b). Still, the main target of the results shown here is to test if hurricanes significantly affect local economic activity on OFCs. Additionally, results on non-OFCs are presented. This provides the baseline against which to compare reactions in financial data.

Using the monthly nightlight dataset outlined in the data section, figure 6 shows the development of average nightlight intensity of Caribbean islands around the dates of hurricanes Irma and Maria in September 2017 (vertical line). Hurricane Irma appeared on the 30th of August 2017 and hurricane Maria dissolved on the 30th of September 2017. Data for islands affected by the storms are averaged in the green line which exhibits a significant drop after the hurricanes. The red line averages nightlights in non-affected islands and shows no decline. Pre-hurricane treands are quite comparable and never significantly different from one another. All series are standardized by country and then averaged within the two groups. In levels, the associated drop registers at around one third of nightlight observed (see Appendix figure A.2 for the raw data).

During the time span of available nightlight intensity data, eleven hurricanes classified as disasters in the Emergency Events Database hit the Caribbean. Since nightlight data is available

Figure 6: **Impacts of hurricanes Irma & Maria on nightlight intensity**



Notes: The figure plots average nightlight intensity in the sample starting in 2016 till the end of the sample. The vertical line indicates September 2017 when hurricanes Irma and Maria hit the Caribbean. Countries are categorized into affected (green) and non-affected (red). All series are standardized by country to eliminate level effects before being averaged within the two groups.

for every jurisdiction under consideration and since these hurricanes hit different jurisdictions at different time points, a panel analysis can exploit within variation of a single island with a control group that varies over time. In what follows, I provide panel evidence on average effects. Reactions to hurricanes are investigated in a standard panel regression of the form:

$$log(lightmean)_{it} = \alpha_i + \gamma_t + \sum_{k=0}^{K}(d_{it+k}) + \epsilon_{it} \tag{2}$$

Where the log of the mean of the nightlight intensity in country i at time t is regressed on a country intercept α_i, year-month dummies γ_t and treatment dummies d_{it} that take value 1 during and after the time of the hurricane for a number differing across lag specifications k. Table 3 shows the results with every regression coefficient being the results of a separate regression. The first column shows results in the entire sample, column 2 shows results for OFCs only and column 3 reduces the sample to non-OFCs as a 'real-world' comparison. The first row confirms a strong negative effect of hurricanes on impact of 19-29% of nightlight intensity across all islands in the sample (Caribbean and Pacific).

Table 3: **The impact of hurricanes on nightlight intensity**

	Dependent variable:		
	log(lightmean)		
	all	OFCs	non-OFCs
	(1)	(2)	(3)
hurricane (k)	-0.248^{**}	-0.335^{*}	-0.213^{***}
	(0.101)	(0.191)	(0.062)
hurricane (k : k + 2)	-0.287^{***}	-0.326^{*}	-0.234^{**}
	(0.099)	(0.173)	(0.111)
hurricane (k : k + 5)	-0.198^{***}	-0.210^{**}	-0.177^{**}
	(0.062)	(0.097)	(0.071)
country f.e.	Yes	Yes	Yes
year-month f.e.	Yes	Yes	Yes
Observations	2,187	1,379	808

Notes: Each coefficient is the result of a separate regression. Column 1 shows results in a panel including all countries, column 2 reduces the sample to only offshore financial centers (OFCs) and column three to non-OFCs. The first row shows reactions to a treatment dummy taking value 1 in the month of the hurricane. The second row includes the first two months after a hurricane in the dummy and the third row the first five months after the hurricane hit the island. Heteroskedasticity and autocorrelation robust standard errors are provided in parentheses.
*p<0.1; **p<0.05; ***p<0.01

The second row shows results of a hurricane dummy that includes the first two months after hurricane impact in the effect. No serious reduction of the effect is visible, if anything, the effect is stronger in the entire sample. This indicates that the impact of hurricane does not die out quickly, in line with existing research that shows recovery periods of at least half a year (Ishizawa et al., 2017; Mohan and Strobl, 2017a). Extending the treatment duration to six months still shows significant results but effect are somewhat weaker indicating that recovery is taking place. Here, effects converge at around −20% of nightlight intensity, still a significant drop if nightlight is indeed a good indicator of economic activity.

Both evidence on hurricanes Irma and Maria as well as the full panel specification thus lead to the same conclusions: Hurricanes do hit economies in the Caribbean and the Pacific and are associated with a significant drop in nightlight intensity of $20-30\%$. These impacts are visible to a similar extent both in OFCs and non-OFCs and only start to die out half a year after the hurricane hit. I interpret these results as the baseline impact of local economic activity on island economies. In the next section, the second step of the analysis is provided: the reaction of financial variables.

4.2 The impact of hurricanes on financial positions

The negative effect of hurricanes on nightlights verifies the first part of the identification strategy: The impact of hurricanes on local economic activity in OFCs is strong and sustained over several months. Also, no discrepancy to the 'real world' is visible as the comparable impact in non-OFCs shows. Here, I first provide results of hurricane shocks on foreign bank loans to and assets in the jurisdiction in question. Such mirror claims are available for 18 OFCs and 14 non-OFCs in the sample of small island economies prone to hurricanes introduced in the data section.

4.2.1 Evidence on BIS mirror claim data

A drop in a GDP proxy of around 20-30% for at least 6 months is a catastrophic event. Maintaining the identifying assumption that banks and NBFIs on OFCs cannot completely insulate themselves against such shocks, some reaction in variables capturing financial activity is expected. Banks and NBFIs could reduce their activities as the result of evacuations, power outages and infrastructure breakdowns. Foreign banks and investors should react to such changes, at least marginally. Before turning to investor reactions, results on BIS mirrorclaims are provided here. These claims include loans to banks and NBFIs as well as assets held by banks against OFCs. Loans could be reduced either because local actors demand less loans or because foreign actors are less likely to provide them. A shedding of assets would also indicate a loss of confidence of foreign banks. In any case, a drop in mirrorclaims would indicate less active participation in the international bank market both by OFC's banks and NBFIs.

As reactions of nightlight intensity data shows, hurricane impacts are visible for at least half a year which validates the use of a quarterly dataset, the lowest time frequency available from the BIS. Both aggregate mirror claims as introduced in the data section and the original bilateral data, both reported by 20 large economies including mostly OECD countries and excluding island economies.[13]

[13] These reporting countries are: Australia, Brazil, Canada, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Italy, Japan,South Korea, Mexico, Netherlands, Philippines, Sweden, Taiwan, United States, and South Africa.

$$ihs(claims)_{iq} = \alpha_i + \gamma_q + \sum_{k=0}^{K} (d_{iq+k}) + \epsilon_{iq} \quad (3)$$

Where q denotes the quarter in question, i the island against which claims are reported and k the time period of the (lag of the) hurricane.

Table 4: **The impact of hurricanes on BIS mirror claims**

	Dependent variable:							
	log(mirrorclaims)							
	ofc Caribbean Sample		ofc Caribbean + Pacific		non-ofc Caribbean Sample		non-ofc Caribbean + Pacific	
	aggregated	bilateral	aggregated	bilateral	aggregated	bilateral	aggregated	bilateral
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
hurricane_{k-1}	−0.047	0.048	−0.085	0.053	−0.028	−0.068	0.003	−0.077
	(0.104)	(0.101)	(0.073)	(0.082)	(0.025)	(0.087)	(0.044)	(0.069)
hurricane_{k-2}	0.003	−0.034	−0.035	0.008	-0.123^{***}	−0.043	−0.059	0.024
	(0.134)	(0.104)	(0.085)	(0.086)	(0.033)	(0.130)	(0.065)	(0.084)
hurricane_{k-3}	−0.077	0.096	−0.097	0.110	-0.173^{***}	−0.100	-0.162^{**}	−0.019
	(0.185)	(0.093)	(0.124)	(0.083)	(0.034)	(0.090)	(0.081)	(0.070)
hurricane_{k-4}	−0.172	−0.007	−0.118	0.040	-0.156^{***}	-0.195^{**}	-0.196^{***}	-0.110^{*}
	(0.162)	(0.100)	(0.118)	(0.084)	(0.036)	(0.089)	(0.050)	(0.065)
hurricane_{k-5}	−0.166	0.016	−0.102	0.057	-0.123^{**}	-0.263^{**}	-0.219^{***}	-0.173^{***}
	(0.152)	(0.095)	(0.097)	(0.082)	(0.053)	(0.109)	(0.062)	(0.062)
hurricane_{k-6}	−0.070	0.049	−0.124	0.063	-0.141^{***}	-0.216^{***}	-0.213^{***}	-0.096^{*}
	(0.163)	(0.092)	(0.103)	(0.080)	(0.042)	(0.069)	(0.054)	(0.056)
country / countrypair f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year-qtr f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	302	2,674	382	3,005	112	950	302	2,194
R^2	0.102	0.017	0.102	0.021	0.329	0.070	0.162	0.029

Notes: Shows reactions of mirror claims to hurricane treatment dummies taking value one in the quarter specified in parentheses. Columns 1 and 2 show reactions of claims against all counterparties in offshore financial centers (OFCs) in the Caribbean. The first column shows aggregate mirrorclaims, the second is based on bilateral data. Columns 3 and 4 add the Pacific part of the sample in the same specifications. Columns 5-8 repeat the same specifications for the sample of non-OFCs with columns 5 and 6 again showing the reaction of Caribbean islands both aggregated (column 5) and bilateral (column 6) and column 7 and 8 add pacific islands to the sample. Heteroskedasticity and autocorrelation robust standard errors are provided in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Table 4 shows the results for six lags of the hurricane impact over four different samples. The first two columns provide results on the Caribbean OFCs in the sample. Column 1 uses mirrorclaims aggregated by OFCs in sample balanced on the second quarter of 2011 as introduced in figure 4 above . Column 2 uses the same data but unbalanced and disaggregated for each reporting country. The second column employs countrypair fixed effects instead of country fixed effects. Both columns show entirely insignificant results with coefficients close to zero, especially in the bilateral panel. The picture doesn't change when the sample is extended to include pacific

OFCs in the same setup (columns 3 and 4). There is no reaction of financial activity targeted at offshore financial centers. Comparing this non-result to the statistically significant drop of 20-35% in nightlight intensity on OFCs is striking and casts some doubt on the assertions OFCs concerning the connection between their bank activity and local human capital.

To verify the identification strategy, column 5 changes the sample entirely. Here, a 'real-world' alternative is investigated: claims against non-OFCs. In line with expectations and with the identifying assumption that banks and NBFIs cannot insulate themselves completely, positions do react here. Effects here are statistically significant and economically meaningful. Effect sizes are smaller than those observed on nightlights so some insulation seems plausible. Nevertheless, declines of 12-17% are visible for the quarters after hurricanes. Columns 6 again provides results of a bilateral sample without aggregating banks claims. Here, hurricanes lead to a significant reduction in bank claims against affected non-OFCs of 12-26%. Columns 7 and 8 add the Pacific islands to the sample and confirm these results.

If indeed local legal, administrative, or banking skills are useful for international customers, it is an open question why the positions and lending activities of international banks to OFCs are not affected by hurricanes that reduce economic activity by a third. Instead, these results suggest that financial activity in OFCs is detached from local economic activity.

4.2.2 Investor responses

This section aims to establish directly if an investor response is visible in the data. Since OFCs are integrated internationally and some of the banks and NBFIs domiciled there are listed on international stock exchanges, this allows a test of what market participants expect in reaction to hurricanes. I carry out a treatment analysis in the spirit of Kothari and Warner (2007) using hurricanes as a potential shock to the net present value of equities of banks and NBFIs on OFCs. While hurricanes can be anticipated in the short term, the extent of the impact comes as a surprise, especially for the disaster-type hurricanes used here. Using the 395 equity price series introduced in the data section, I first discard returns below the 1st percentile and above the 99th percentile. I then compute daily abnormal returns (AR_{it}) as the deviation of realized returns (RR_{it}) from expected returns (ER_t). For expected returns, I follow convention and use the S&P Global 1200 stock market index (see Johannesen and Larsen, 2016, for a similar setup). Expected returns are therefore not equity specific but realized and therefore abnormal returns are.

$$AR_{it} = RR_{it} - ER_t \tag{4}$$

In equation 4, i denotes the 395 equity price series, and t. Following Johannesen and Larsen (2016), I choose a treatment window of four trading days including the hurricane date and use abnormal returns of the last four trading days before the event as a point of comparison. Average abnormal returns are computed as the simple average of daily abnormal returns. These are then cumulated over the post-treatment window to generate cumulative average abnormal returns which I interpret as the investors response to unexpected hurricane impacts. For statistical inference, I both compare the two four day windows using a simple t-test and use the ratio of post-event cumulative abnormal return over the pre-event standard deviation of abnormal returns (Kothari and Warner, 2007).

Table 5: **Cumulative average abnormal returns after hurricanes**

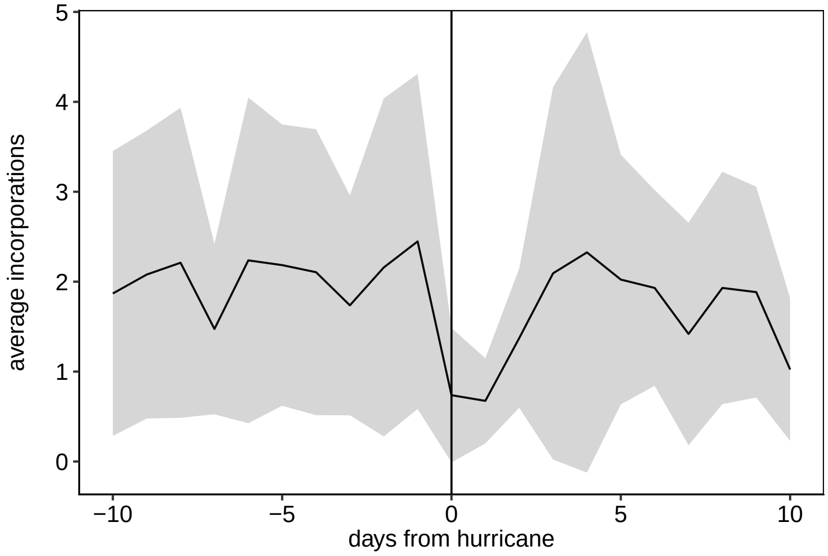
	domiciled in OFCs	domiciled in non-OFC
cumulative average abnormal returns (k=0 : k+3)	-0.556	-1.076***
t-statistic	(1.195)	(3.014)
Kothari Warner (2007) statistic	(-0.674)	(-3.311)

Table 5 shows the results. While cumulative abnormal returns are negative for OFCs, statistical significance is not visible on either of the two tests, indeed, conventional critical values are quite far off. As before, I provide the reaction of non-OFCs not as a direct comparison but as a benchmark showing that in a real-world sample, are visible. This evidence is in line with the results shown for mirrorclaim data: foreign investors do not seem to perceive an exogenous shock that reduces local economic activity by 30% and takes half a year to die out on average as detrimental to their portfolio of OFC bank and nfi stocks. This is especially stunning when compared against the strong real-world drop in stock returns in non-OFCs.

4.2.3 Evidence on Company Registrations

Incorporating shell companies is part of the bread and butter of an OFC and an activity that almost by definition requires local authorities to act if only to sign documents. Company incorporation identifies an action by a an individual or a service provider in corporation with local authorities. At the very least, the official recognition of incorporation should take place on the island in question. More than 300.000 incorporation events are available from the leaked ICIJ data introduced in the data section. Here, time series on total incorporation per day are used to see how such activity develops over time. Even if the financial service provider resides elsewhere, incorporating a firm arguably includes functioning communication with the island, electricity and a responsive administration. While the incorporation data used in this section is much smaller in scope than the datasets employed above, some storms do take place during the time spans observed. Still, results showed in this section are not generalizable to the same extent. Only a few jurisdicitons have leaked incorporation events of reasonable frequency before and after hurricanes. Therefore, results here are driven mainly by St. Kitts & Nevis and Barbados.

Figure 7: **Impact of Hurricanes and Typhoons on all Incorporations**



Notes: Shows mean daily incorporations and 95% confidence intervals 10 days before and after hurricane strikes (vertical line) in the sample.

As figure 7 shows, during the days of a hurricane, the number of incorporations does decrease. It shows mean incorporations and a 95% confidence intervals for a +/- 10 day window around hurricanes with hurricanes taking place at time 0. Recovery is very fast, consistent with an interpretation that most of the work in company incorporation is not done on the island. Still, a short but pronounced effect of the hurricane is visible. While this evidence is limited to a few jurisdictions and should therefore not be overstated, it seems that incorporations are a potential candidate for activity that is still connected to administrative processes on OFCs.

5 The relation between finance and the real economy in OFCs and non-OFCs

The preceding section has established a striking absence in reactions of financial positions on OFCs to hurricanes. The identifying assumption that allowed any interpretation of these results was that banks and NBFIs cannot completely insulate themselves against hurricanes. In this section, I leave the natural experiment aside and instead provide descriptive indications of a disconnect between financial and local economic activity on OFCs.

The large financial positions that are documented in the data section potentially lead to high income in the form of fees or taxes that can be substantial even with very low tax rates due to the inflated foreign tax base relative to small island economies (see Zucman (2013) and Tørsløv et al. (2018) for a similar point regarding European tax havens). It is, however, an open question how these funds are used and to what extent they end up in the local economy. The results presented so far document a stunning discrepancy between *responses* in local economic activity and international financial positions to the exogenous shocks of hurricanes. In this section, I make use of the nightlight and BIS mirror data to investigate the direct relationship of these variables.

Having access data on real economic and financial activity in small island economies, it is possible to provide a first indication. Satellite data on nightlights has been used in the development literature to approximate local economic activity (Henderson et al., 2012) and mirror claims measure the international financial integration of banks and non-bank financial institutions providing financial services. Using these two data sources at quarterly frequency, figure 8 plots average nightlights over international bank loans[14]. Both variables are transformed using the log-equivalent inverse hyperbolic sine transformation to retain negative and zero observations[15]

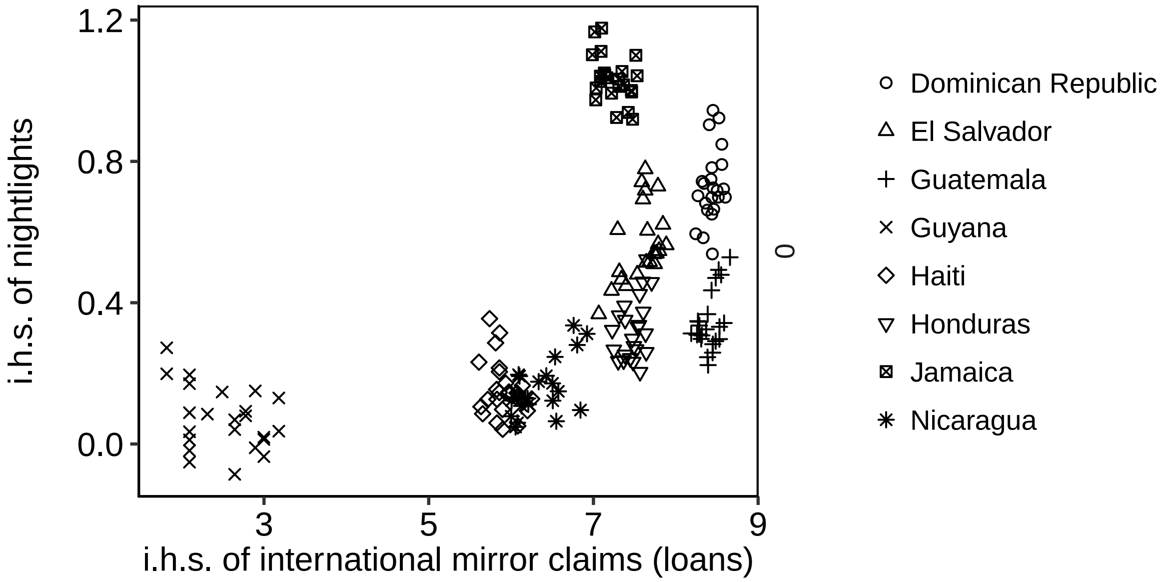
The top panel shows a positive relationship for non-OFCs both between countries as well as within countries. This relationship is not linear but increases over mirror claims. Maintaining that nightlights proxy real economic activity, this image is intuitive: higher foreign capital positions are associated with higher local economic activity. However, no such relationship is visible in the OFC part of the sample as shown in the bottom panel of figure 8: neither between nor within jurisdictions. This is an interesting finding in its own right: it suggests that foreign financing in the form of loans and assets held by foreign banks is not directly associated with higher economic activity in OFCs. Again, this is visible both between countries, where the

[14]Total bank claims show a similar picture but loans are a cleaner measure of reliance in and integration with the local financial industry.

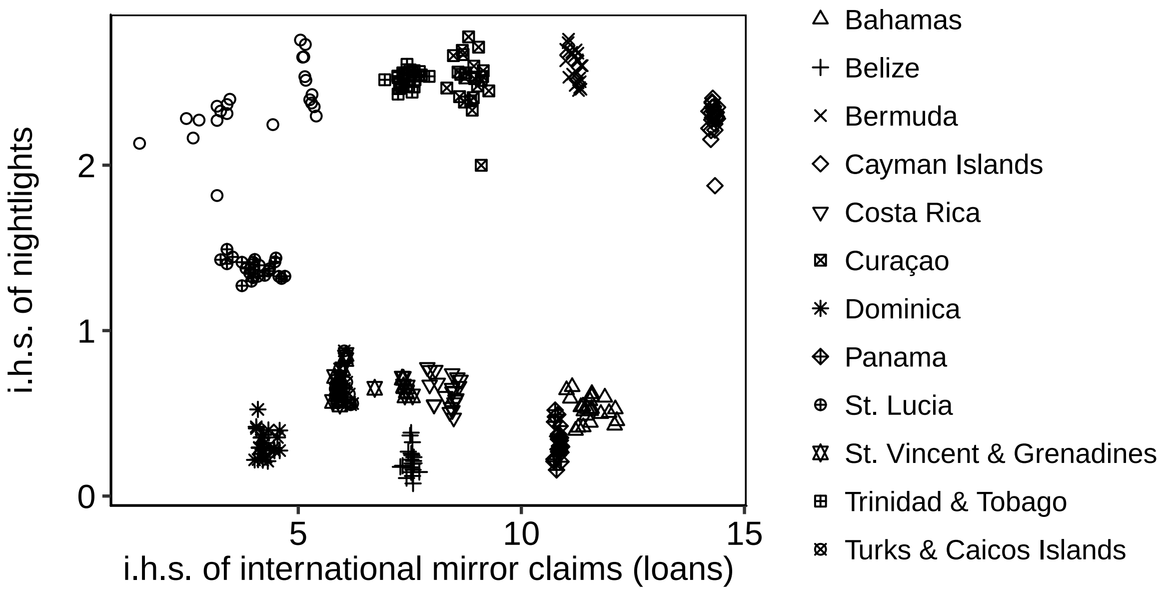
[15]The inverse hyperbolic sine transformation is calculated as: $ihs(x) = log(x + (x^2 + 1)^{1/2})$.

Figure 8: **The disconnect between nightlights and foreign capital**

Non-offshore sample



OFC sample



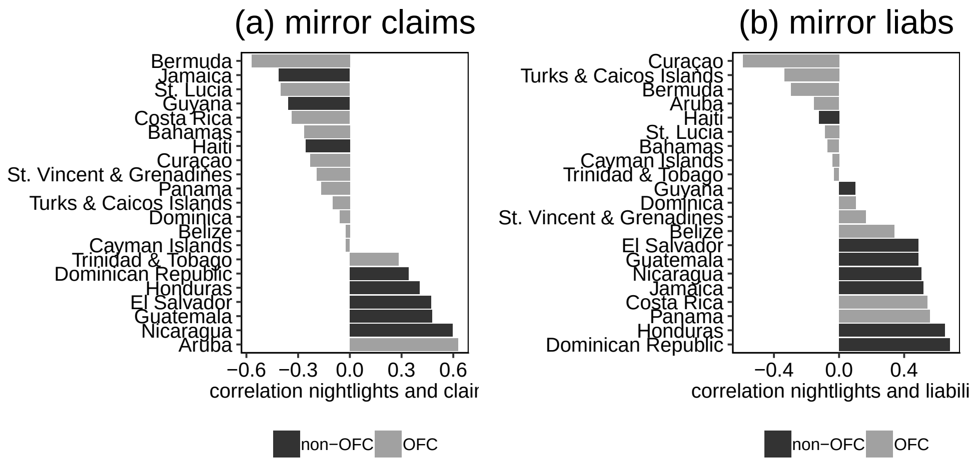
Notes: Both figures plot the inverse hyperbolic sine of nightlights over the inverse hyperbolic sine of the sum of international bank claims by all reporting non-OFC economies. The sample is limited by the availability of offshore mirror claims. Panel (a) shows the non-offshore part of the sample with a positive relationship of both variables both within and between countries. Panel (b) shows the OFC part of the sample where no such relation is visible.

bottom panel shows a random cloud and within countries as no relationship is visible in data on single jurisdictions. The 'real-world' relationship thus disappears when focusing on OFCs.

A similar picture emerges when looking at within country correlations only. Figure 9 (panel a) shows correlations of nightlights and mirror claims for the countries for which both variables are available. Again, OFCs such as the Cayman Islands, Panama or the Turks & Caicos Islands exhibit close to a zero correlation while the non-OFC part of the sample by and large shows positive correlations. This is confirmed by foreign mirror liabilities (panel b). While these correlations are not unanimous, a tendency is visible.

Interpreting this measure allows a different understanding of OFCs than the offshore intensity measures proposed in Fichtner (2014, 2015) who employ levels of foreign capital over GDP. The measure here compares within country correlations over the sample length. Although not causal, a zero relationship here casts some doubt on a direct translation of foreign capital inflows into economic activity on OFCs. The measure in figure 9 is thus more useful for classification but less useful for ranking different OFCs against each other.

Figure 9: **Within correlations of nightlights and international bank positions**



Notes: This figure plots within-country correlations of the the inverse hyperbolic sine of nightlights over the inverse hyperbolic sine of the sum of international bank claims (panel a) and liabilities (panel b) by all reporting non-OFC economies. Light grey bars show OFCs and dark grey bars show non-OFCs.

The disconnect between local economic activity and international financial activity on OFCs is thus not only visible in reaction to shocks but also in the raw data. In both cases, non-OFCs exhibit a positive correlation of both variables and a drop after a hurricane. OFCs, on the other hand, show neither. All this in spite of the very similar impact of hurricanes on local activity as measured in nightlights over these two country groups.

6 Conclusion

Although offshore finance remains a hotly debated topic in academic and policy circles, little empirical evidence is available to illuminate or quantify what really happens in such jurisdictions. Despite recent regulation facilitating international information exchange and increased pressure on offshore financial centers (OFCs) to comply with such regulation, capital positions in OFCs do not decline raising the question what constitutes these.

Building on several data sources, this study attempts to shed some light on this question. A newly constructed monthly nightlight dataset for Caribbean and Pacific island economies is combined with mirror claim data by the BIS, equity data on banks and NBFIs domiciled there and leaked data on incorporations in OFCs.

In a first set of results, this contribution exploits the natural experiment of re-occurring hurricanes and typhoons in the Atlantic and the Pacific to determine if financial activity registered to offshore islands is physically taking place there. A significant impact of around -20 - -30% of hurricanes on nightlight intensity is visible. These effects last at least six months. This negative reaction is visible both in OFCs and non-OFCs and robust to different time frames. It is also quantitatively in line with the literature on natural disasters.

However, when investigating data connected to the activity of banks and non-bank financial institutions (NBFIs) on OFCs, no reactions are visible. Also, international investors holding equity of such institutions to not seem to react. As a 'real-world' baseline, non-OFCs are investigated and do show significant drops in bank claims reported against them. Also, institutions domiciled there exhibit large negative abnormal returns. The only variable on OFCs where reactions to hurricanes are visible are leaked company incorporation data taken from the corporate registries of six OFCs. Here, an albeit limited reaction is visible. This indicates that some activity does take place on OFCs but it seems to have much less to do with banking and much more with putting a stamp on an incorporation document. Compared to the several month-long impacts of hurricanes on nightlights, these results are striking.

In a second more descriptive set of results, a disconnect between finance and the real economy is observed in OFCs but not in non-OFCs. Indeed, OFCs tend to bunch around a zero within country correlation of financial and local economic activity. The same is true for between-country correlations. This suggests that the potentially large fees and services accruing in OFCs do not immediately translate into economic activity on the island raising the question who benefits from them.

Taken together, these results suggest that the positions booked through offshore financial centers are not connected to financial service activity that is physically present in OFCs. This casts doubt on the interpretation of OFCs as contributors of a certain set of skills and human capital, improving the efficiency of the international financial system. Instead, it is consistent with an interpretation that interprets OFCs as mostly providing opportunities for regulatory arbitrage.

7 References

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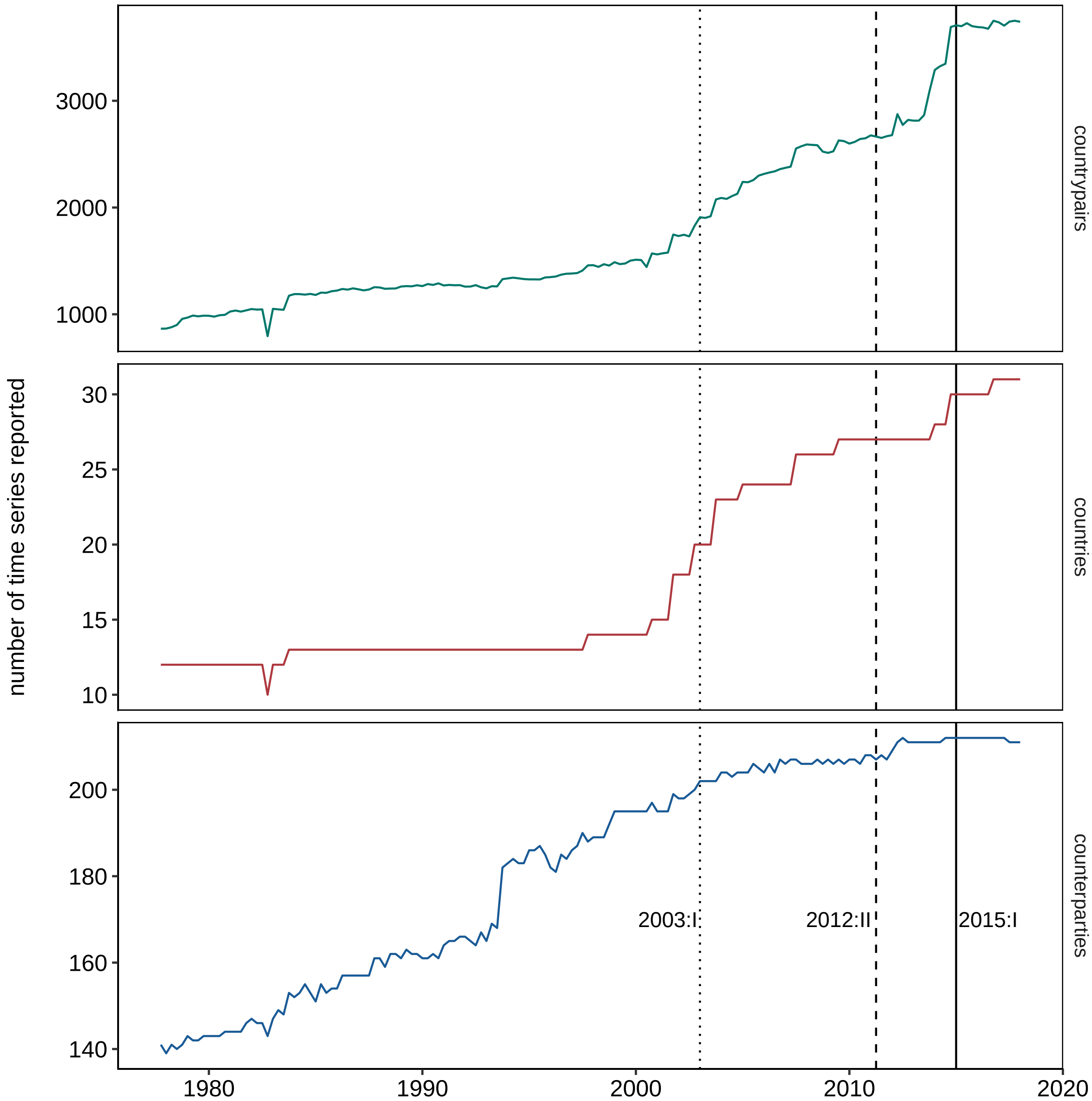
Appendix

Appendix A.1 Coverage of bilateral BIS data over time

The locational banking statistics used in the main text are derived from reports of a reporting country against a large number of counterparties. The coverage of this dataset changes along both dimensions. A continuous increase is visible over time as shown in figure A.1. The top panel shows the total number of countrypairs available starting in 1977 with the earliest reports. The middle and bottom panels show the underlying developments on the country and counterparty dimension. The number of countrypairs almost doubles between the earliest balanced series (starting in 2003:I, vertical dotted line) and the data used in the main text (starting in 2011:II, vertical dashed line).

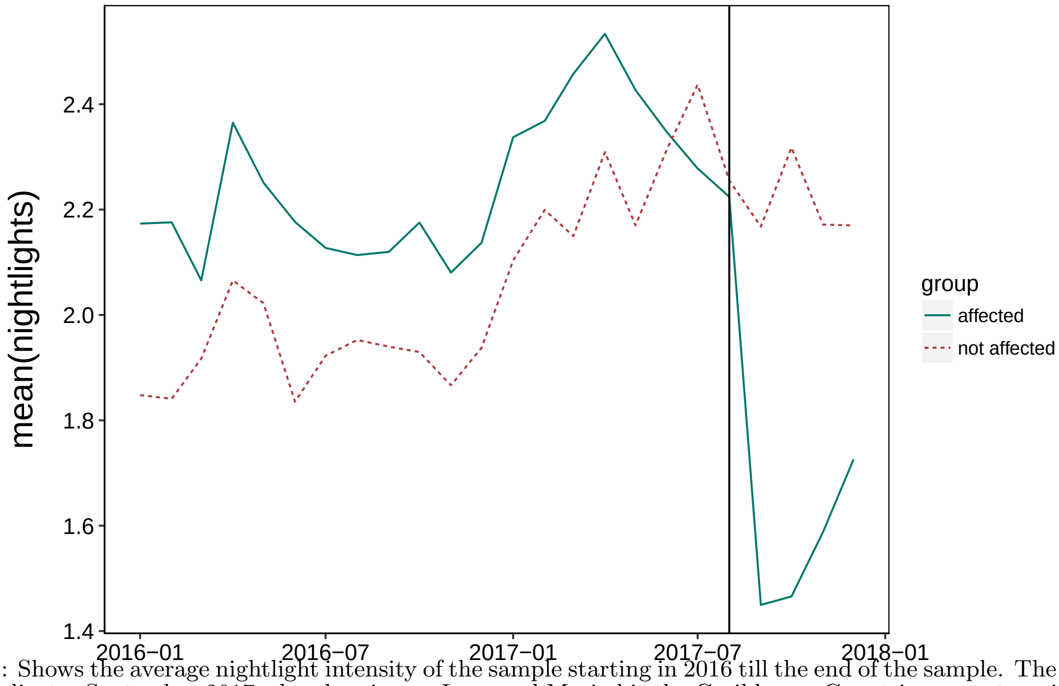
However, as was shown in figure 4, this increase is neither changes the level nor the time dynamic of total reported mirror claims against one counterparty drastically. The large OECD countries that report the highest positions start reporting early in the sample and the large number of countrypairs where data becomes available late in the sample (the vertical dashed line in figure A.1 shows the panel available for balancing in 2015:I) report relatively small positions that follow similar trends.

Figure A.1: LBS time series availability



Notes: The three panels show the availability of bilateral time series on international claims against all counterparties in the BIS' locational banking statistics. Observations are counted on the vertical axis when reports are available. The top panel shows total available countrypairs. The middle panel shows the number of reporting countries that report bilaterally (excluding those countries that only report against all countries aggregated). The bottom panel shows the total number of counterparties bilaterally reported against. The three vertical lines indicate the times at which balanced series are created for the main analysis: 2003:I, 2012:II and 2015:I as mentioned in the main text

Figure A.2: Impacts of hurricanes Irma & Maria on raw nightlight data



Notes: Shows the average nightlight intensity of the sample starting in 2016 till the end of the sample. The vertical line indicates September 2017 when hurricanes Irma and Maria hit the Caribbean. Countries are categorized into being hit and not being hit by these hurricanes.