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The Elusive Banker:
Using Hurricanes to Uncover (Non-)Activity in Offshore Financial Centers

Abstract

This paper studies financial service provision booked through offshore financial centers (OFCs). Based on several novel data sources and recent advances in event study methodology, I exploit the natural experiment of re-occurring hurricanes hitting small islands and compare local reactions to reactions in financial service activity. I find that local conditions, captured by monthly satellite data on nightlight intensity, deteriorate significantly for nine months. However, in OFCs, the international bank sector does not react. Non-OFC islands on the other hand do show strong negative reactions. Similar (non-)reactions are visible in equity prices. Additionally, a link of OFC service provision to activity in London, Tokyo, and New York is visible in leaked data. Finally, a long term relationship between offshore finance and local development is absent, but only on OFCs. These results indicate that international regulation attempts that aim at forcing OCFs to provide information on financial service activity could be targeted better, they show that we mis-allocate financial risk to OFCs, and they cast doubt on offshore finance as a valid development strategy.

JEL-Codes: H260, G150, C820.

Keywords: offshore finance, international bank claims, nightlights, hurricane impacts.

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1. Introduction

Small Offshore Financial Centers (OFCs) are home to at least 40% of international capital[1] and their importance is still increasing (Alstadsæter et al., 2018; Milesi-Ferretti and Lane, 2017). Researchers and journalists have shown that such capital is connected to profit shifting, tax evasion, and other illicit financial flows. This has focused attention on tax evading individuals and profit shifting firms. However, little is known about the offshore financial service sector that intermediates all of these funds by providing wealth management services, managing multi-level company structures, or reacting to policy measures. OFC financial institutions themselves argue to be providing skilled human capital and innovative legal and financial services that successfully attract international capital. Indeed, OFCs are economically open, provide sophisticated communications infrastructures, and perform well on governance indicators (Dharmapala, 2008; Dharmapala and Hines, 2009). Also companies, fund managers, and official government aid institutions argue that OFCs play a vital role in their international investment strategies by providing a set of unique skills and services.[2]

Policy makers seem to agree implicitly. Several international policy measures trying to regulate offshore finance are based on information exchange from one country to another. An OFC should thus collect and provide information on its financial service industry, for example the bank account of a potential tax evader. If this bank operates on the OFC, it could be audited or searched there. The policy would be well targeted. But are financial intermediation services actually carried out in the OFC where they are booked? Can they therefore be connected to a comparative advantage of OFCs to provide them? If not, where do they take place? And what are the implications of such elusive bankers for offshore finance as a development strategy for small economies? Here, answers to these questions are provided.

In this paper, I test if international financial services booked on small island OFCs can be traced back to local activity. Using recent advances in event study methodology, I exploit natural disasters in the form of hurricanes hitting such island economies and compare local impacts, measured using satellite data, to impacts in international financial service provision, measured in several new datasets. In both cases, I compare reactions of OFCs to a sample of non-OFC islands to potentially falsify the identification strategy. Results show that local conditions deteriorate significantly in both samples after hurricanes hit. Despite such impacts, the financial service sector is unaffected on OFCs both using data reported by international banks and using equity price data. On non-OFCs, however, also financial service activity deteriorates

[1] Based on the BIS data and the OFC list introduced in the main text, as well as Zucman (2013) or Damgaard et al. (2019).

[2] The German official development aid, for example, explains its participation in investment funds on Mauritius along these lines. These funds are recorded here: https://www.deginvest.de/International-financing/DEG/Download-Center/Jahresberichte/, last accessed July 20th, 2020.

significantly. These results suggest that the financial service activity booked in OFCs is not, in fact, local. Selective evidence based on leaked incorporation data instead links OFC financial service activity to Tokyo, London, and New York. Finally, I do not find a direct relationship between local development and financial service activity, casting doubt on offshore finance as a valid development strategy.

Studying the financial service sector on OFCs was previously inhibited by two non-trivial problems. First, researchers have to identify reactions of activities that are oftentimes shrouded in secrecy or at least not officially recorded. Second, data for OFCs, especially small island economies, is either unavailable, unreliable, or inflated by the financial service sector itself. Here, I make progress in both areas.

Identifying effects of international policy measures on OFCs is difficult because such policy measure are usually implemented as reactions to increasing capital on OFCs. Here, I use hurricane impacts as exogenous shocks to small island economies, circumventing such policy endogeneity. About half of all offshore capital is booked through islands economies such as the Cayman Islands, the British Virgin Islands, or the Cook Islands. Based on sample choices outlined in detail below, 56 inhabited small island economies are located in the 'hurricane alley' of the Caribbean and the Pacific and Indian Oceans. Defining OFCs as jurisdictions with high secrecy regulations and low to zero tax rates for foreigners and using common OFC lists (Gravelle, 2015; Johannesen and Zucman, 2014)), 27 of those are OFCs islands. When hurricanes hit (hurricanes, typhoons, and cyclones are subsumed under 'hurricanes' here) these islands and a strong local effect can be shown, the financial service industry active on the island should be affected. This is confirmed in reaction of the 29 non-OFC islands. The identifying assumption this identification strategy relies on is that OFC banks cannot completely insulate themselves from the same hurricane shocks that non-OFC banks react to.

The problem with this identification strategy is that data on small islands is scant. I introduce a number of new data sources and use existing ones in new ways to make progress. First, I construct a monthly nightlight dataset with global coverage based on satellite images. These data are constructed both for entire jurisdictions in the sample and as well as their sub-national regions. Nightlights proxy physical conditions on the island in question and are used as an impact measure in the main results. On average, a hurricane leads to decreases in nightlight intensity of close to 20% for the first nine months after impact both on OFCs and non-OFCs. Recovery takes six months to one year. Both the impact and the recovery effects are in line with the literature on natural disasters (Mohan and Strobl, 2017; Strobl, 2011, 2012). An R package allowing other researchers to build such data for any geospatial unit on the planet has already been uploaded.[3] To the best of my knowledge, such satellite data has not been used so far in

[3]This package allows the construction of nightlight statistics beyond the small islands used in

the study of offshore finance.

As a first measure of financial service activity, I propose a new way to use the Locational Banking Statistics (LBS) of the Bank for International Settlements (BIS). If an American bank lends to a bank, maybe even its own subsidiary, on the Bahamas, it reports this claim to its central bank in quarterly reports. The Federal Reserve System will aggregate these positions for all American banks and report an aggregated bilateral time series of total American bank claims against the Bahamas to the BIS. Adding these bilateral series for all BIS reporting countries leads to a total 'mirror claims' series that measures the funding received by the Bahamas from internationally active banks. Due to the high leverage ratios of banks and non-bank financial firms, such mirror claims provide a good proxy for financial service activity. When financial operations on the Bahamas decline, so will foreign bank funding. Indeed, in the non-OFC part of the sample, mirror claims are reduced by 33.6% after hurricanes hit suggesting decreased financial activity on the island. However, despite the significant impact on the local economy visible in nightlight data there are virtually no effects of hurricanes on financial activity in OFCs. Results are statistically insignificant, coefficients are very close to zero and do not exhibit sign certainty. Such evidence is not consistent with a local presence of financial service activity on OFCs significant enough to be visible in macroeconomic data.

To verify that the results are not driven by particularities in the BIS data, a first set of extended results uses the same identification strategy in a dataset of equity price data from Bloomberg. Results show that international investors of banks and non-bank financial institutions domiciled in sample islands react analogously. Equity prices of financial service providers domiciled in OFCs do not react after hurricanes hit while equity of financial service providers domiciled in non-OFCs exhibit significant negative abnormal returns. The non-OFC result confirms recent work about hurricane impacts on stock markets (Kruttli et al., 2019).

A second set of extended results shows that service activity on OFCs could be connected to activity in London, Tokyo and New York. Among other information, the 'Paradise Paper' data leak included the incorporation dates of the firms in six OFC corporate registries. I collect these incorporation dates into daily national time series of company incorporations - including shell companies. These OFC incorporation series show strong decreases during public holidays in London, Tokyo, and New York that are normal work days on the OFCs in question. This suggests a connection of OFC service provision to activity in these three financial hubs. Due to data limitations, these results are necessarily selective but provide an indication for future research about where to look for the activity that seems to be missing in OFCs.

If financial service activity is not local, does the local economy benefit from it? A third

this study. It was prepared and is maintained together with Mark Toth and available at: www.github.com/JakobMie/nightlightstats.

set of extended results goes beyond natural experiments and compares the relationship between nightlights and the financial sector directly, using nightlights as a measure of economic development. I find no direct correlation between nightlights and financial service activity, but only on OFCs. This is true both within and between islands. For non-OFCs, on the other hand, a positive correlation between the two is readily observable. This suggests that long term economic gains from offshore finance are absent for the local economy and raises questions about offshore finance as a reliable development strategy.

Related Literature: By focusing directly on financial service provision on OFCs, this study fills an important gap in the literature. The rapidly developing literature on international tax noncompliance has almost exclusively focused on customers of such services: – tax evaders, profit shifting multi-national enterprises (MNEs), or corrupt officials. The financial intermediary that makes all of this possible is neglected. However, both tax evaders and profit shifting companies rely on financial intermediaries to incorporate the shell company, manage the offshore trust, and react to policy measures targeting such practices (documented in Omartian, 2017). Instead of focusing on this sector, studies rely on indirect identification strategies and leave the precise workings of an offshore financial structure to qualitative illustrating examples. To see this, consider the following strands.

Research on international tax evasion detects reactions to policy measures that affect tax evaders on their bank deposits in tax havens (Johannesen, 2014; Johannesen and Zucman, 2014; Langenmayr, 2017; Menkhoff and Miethe, 2019) or on the final investment from the tax haven (Hanlon et al., 2015; Heckemeyer and Hemmerich, 2020). The literature on other illicit flows via OFCs proceeds analogously (Andersen et al., 2017, 2020). Only the first or final investment of the agent is studied, where the tested treatment affect her decisions. The OFC intermediary is used as a source for financial data but its operation is usually not studied.

The literature on profit shifting by MNEs also focuses on the customer of financial services. It shows that firms use subsidiaries in OFCs to avoid taxation (see Beer et al., 2020; Riedel, 2018; Slemrod, 2015, for overviews) but does not investigate who creates and manages these and from where. Banks are mainly studied in their role as MNEs shifting profits themselves (Langenmayr and Reiter, 2017),not as financial intermediaries. Estimates of profit shifting or tax evasion focus on discrepancies in international financial statistics (Clausing, 2020; Tørsløv et al., 2020; Zucman, 2013) or on microeconomic data for multinational firms (Becker et al., 2020; Johansson et al., 2017) without studying how they are created by financial service providers. Coppola et al. (2020) use microeconomic investment data to show the ultimate owner countries of international capital flows, Damgaard et al. (2019) do so for macroeconomic flows. This is a significant step forward to understand ultimate owners of shifted funds but tells us little about how this is managed. Policy evaluations of MNE activity again employ indirect strategies (Clifford, 2019; Dharmapala et al., 2011). All of these approaches abstract from the financial intermediaries that facilitate profit shifting. The theoretical literature in turn has provided models that allow for both interpretations: the cost of an intermediation service could arise offshore or at home (see for example Slemrod and Wilson, 2009, footnote 14 makes it explicit).

This summary of the literature shows a classic light post problem: The usual identification strategies don't bite for the financial sector and data is unavailable. Therefore, the OFC financial sector is not sufficiently studied, a gap this paper starts to fill by providing evidence on its (non-)activities.

At least three important policy conclusions arise from the new evidence I provide here. First, current regulation attempts of OFCs could be mistargeted. If financial intermediaries do not operate on the OFC itself, the island has little chance to counter false reporting by the bank or to collect information. This is, however, exactly the kind of information that country-by-country information exchange aims to get from the OFC. Indeed, preliminary policy evaluations of such policy measures show mixed effects at best (Bustos et al., 2020; Johannesen, 2014; Johannesen and Zucman, 2014; Menkhoff and Miethe, 2019). Such missed opportunities could further undermine the already low confidence that governments are able to tackle tax noncompliance (Stantcheva, 2020). Second, it raises financial stability concerns. Potential risks created in non-OFCs could be underappreciated if they exclude the activity that is booked through OFCs but actually carried out in non-OFCs. A bank that books part of its activity through an offshore subsidiary but is ultimately responsible for its risk would have to be supported by its non-OFC lender of last resort in case of shocks. Third, the results here cast doubt on offshore finance as a valid development strategy for small island economies as it appears to be detached from the local economy. This could explain why, for example, the British Virgin Islands applied for UN emergency food relief after hurricanes Irma and Maria hit it in 2017. The 373,917 companies and 1,499 mutual funds that are registered there could apparently not provide sustenance for its 35,015 inhabitants after an external shock.[4]

As its main contribution, this paper significantly improves our understanding of financial intermediation activities on OFCs. I show that OFC service providers are unlikely to be providing significant financial services on OFC islands. This setup differentiates two factors in the attractiveness of OFCs: Their local competitive edge in providing financial service through skilled human capital, which should react to local shocks, and the regulatory arbitrage opportunities they provide which remain as the only explanation for the high financial sector positions observed there. The results in this paper show that the first factor is negligible which leaves

[4]Data taken from the BVI statistical bulletin 2020Q1, available here: https://www.bvifsc.vg/sites/default/files/documents/Statistical%20Bulletins/q1_2020_statistical_bulletin_final.pdf, last accessed 17th of August 2020.

regulatory arbitrage to explain financial sector positions in OFCs. While this is a contribution in its own right, it has more important implications by indicating that the financial service industry is not well understood and regulated sub-optimally, leading to the policy conclusions summarized in the last paragraph.

The paper also provides a number of secondary contributions. First, I show that identification strategies beyond the usual tax changes or policy measures targeted at tax evasion or profit shifting are feasible to study offshore finance. Using re-occurring hurricanes as exogenous shocks additionally circumvents the policy endogeneity issue endemic to the literature. Second, I provide a number of new datasets hitherto unavailable or unused in the study of offshore finance. The monthly nightlight dataset for small island economies is the first time satellite data is used to study offshore finance, to the best of my knowledge. Three proxies of financial service activity together provide the most comprehensive image of OFC financial service activity available so far: 'mirror claims', equity prices, and daily incorporation series from leaked datasets. Since none of these data sources rely on data voluntarily reported by OFCs themselves, data reliability concerns are mitigated here. Third, I provide a contribution to open science as an R package facilitating the construction of nightlight data has already been made available online. Finally, for researchers working on offshore finance, I show that the assumption of no significant activity on OFCs can be extended to the financial sector and models including financial service cost should assign this cost to the home economy of the tax evader or the MNE.

The study proceeds as follows. Section 2 outlines the identification strategy based on hurricane impacts in detail. Section 3 introduces sample choices and the data sources: geo-spatial data on nightlight intensity, hurricane data, and data measuring financial service activity. Section 4 introduces the methodology and provides the main results on hurricane impacts, comparing the responses of local conditions and international bank positions. In section 5, extended results on investor responses and incorporation data are provided and the direct connection between nightlights and financial service activity is discussed. Section 6 provides robustness tests before concluding remarks are presented in section 7.

2. Identification: The Natural Experiment of re-Occurring Hurricanes

I address the two problems when studying offshore finance, identification and data, in turn. This section focuses on the identification of offshore finance activities: reactions of local conditions and financial service activity to exogenous local shocks.

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). Here, the natural experiment of re-occurring hurricanes provides 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. In the Pacific and Indian Oceans, islands are spread out and regularly hit by typhoons.

Only storms categorized as natural disasters by the emergency events database introduced below are used here. Disaster type hurricanes lead to extended power outages, disabled infrastructure, evacuations, flooding, and direct casualties on such islands. Hurricane Irma in autumn 2017, for example, directly affected 1.2 million people with wind speeds of up to 295 kilometers per hour, leading to damages of 50 billion USD in the United States alone, and cut electricity for several million inhabitants on Caribbean islands and in Florida (US Office for Coastal Management).[5] The hurricane affected eight OFC territories[6] and five non-OFC islands.[7] Local impacts were substantial. To give a few examples: 90% of all buildings on Barbuda were destroyed, 95% of all houses on Sint Maarten were uninhabitable and the death toll of Puerto Rico reached 4,645 (Kishore et al., 2018).

— Figure 1 about here —

Figure 1 summarizes how these shocks can be used to learn more about OFCs. Assume a hurricane hits an OFC at time t. The top left panel of Figure 1 indicates the potential deterioration of local conditions. The basic identifying assumption now is that banks and non-bank financial institutions (NBFIs) cannot completely isolate themselves from this shock. The magnitude of the effect may differ but the presence or absence of financial service provision as an activity physically carried out in OFCs would be mirrored by a reaction in the top right panel of Figure 1. Physical destruction such as power outages and infrastructure breakdowns impact the working conditions of financial service providers. Non-OFCs (the bottom panel of Figure

[5] Last accessed June 30th, 2020, at: https://coast.noaa.gov/states/fast-facts/hurricane-costs.html

[6] (1) Anguilla; (2) Antigua and Barbuda; (3) Barbados; (4) the British Virgin Islands; (5) St. Lucia; (6) St. Kitts and Nevis, (7) St. Maarten (Dutch Part); and (8) the US Virgin Islands.

[7] (1) Cuba; (2) Guadeloupe; (3) Haiti; (4) Puerto Rico; and (5) Saint Martin (French Part).

1) are investigated as an additional test of this identification strategy: they lend support to interpreting the non-result for OFCs. In effect, testing non-OFCs relaxes the identifying assumption to: Banks and NBFIs cannot completely insulate themselves from hurricanes *when non-OFC institutions are affected*. If hurricanes do not affect the financial sector on OFCs, I take this as evidence that the service is carried out elsewhere and merely booked through the OFC. The differentiation into OFC's and non-OFC's in this study is based on the lists of Gravelle (2015) and Johannesen and Zucman (2014) with robustness checks providing results for different lists from the literature.

The strength of this straightforward identification is the significant number of OFCs and non-OFCs in the Caribbean and in the Pacific that are in hurricane areas and provide rich treatment variation. Its weakness is that for most islands in the sample, neither local conditions nor financial service activity are readily observable. The following data section constructs new datasets that allow an implementation.

3. Data

This section introduces several data sources with large to complete global coverage including small islands. After introducing the sample islands, satellite data on nightlight intensity is used in combination with geo-spatial data on geographic boundaries of the jurisdictions in question to construct a monthly dataset of nightlight intensity. Second, data from the Bank for International Settlements (BIS) on international bank claims reported by major economies is introduced. These positions are reported bilaterally against up to 240 counterparty economies, including the majority of small islands under study here. In the extended results section, two other data sources with less comprehensive coverage are analyzed: Equity prices of financial service providers domiciled in the island economies under study and the leaked corporate registries of six offshore financial centers. These data sources are introduced directly in the respective sections. Crucially none of the data sources employed here requires information deliberately reported by OFCs. This alleviates concerns of misreporting or data quality.

3.1. Sample Selection

There are 104 island jurisdiction on the planet, ranging from military atolls such as the Spratley Islands to the United Kingdom and Greenland. This section outlines the choices needed to reduce this sample to one suitable for identification using hurricanes. First, only islands that are located in the Caribbean, the Pacific Ocean, and the Indian Ocean are used, where hurricanes can be expected.[8] Then, islands that exhibit one of the following characteristics are excluded from the sample: The jurisdiction does not have an iso3 code and thus no geospatial data,[9] it is landlocked (including to a larger island),[10] or it is uninhabited/a pure military base.[11] Next, two choices concerning large islands and island groups are needed. Indonesia, for example, spans large parts of the Pacific. A hurricane hitting it does not necessarily show up in national financial data. Fortunately, the area distribution of island economies is has a clear cut-off point (see Figure A.1.1 in Annex A.1) with no island of an area between 109,238 square kilometers (Cuba) and more than double that size: 244,820 square kilometers (The United Kingdom). The sample is therefore cut at Cuba, dropping larger islands.[12] Finally, island groups that cover a large area due to the presence of islands that are spread out very far are dropped. This choice is based on exclusive economic zones that include the water area between islands of the same island group. Again, there is a natural cutoff-point (see Figure A.1.2 in Annex A.1) between the Solomon Islands (the largest island group still included with 1.5 million square kilometers of exclusive economic zone) and the Cook Islands (2 million square kilometers). After the decision rule on land area, this choice only excludes some very spread out island groups.[13] Table A.1.1 in Annex A.1 provides an overview of all island jurisdictions on the planet as well as, if applicable, the reason(s) for excluding jurisdictions from the sample used in the main results. While the sample is reduced significantly by these choices, it provides a well defined setting to test for hurricane impacts.

3.2. A monthly nightlight dataset for small island jurisdictions

Since data for these islands is scant, several datasets are introduced here and summarized in turn. Satellite data is frequently used by development economists trying to measure economic conditions in remote areas or countries with unreliable national accounts. Henderson et al. (2012) provide a seminal contribution relating nightlight data to economic growth, for a summary see Donaldson and Storeygard (2016). It is worth mentioning that the identification strategy proposed in the last section does not rely on the ability of nightlight data to proxy GDP. Instead, for the main results nightlights are used as an impact measure to test if both OFC and non-OFC islands are affected by local shocks.

— Figure 2 about here —

[8] This excludes islands such as Cyprus and Malta, or the Falkland Islands.
[9] This excludes islands such as the Easter Island or the Azores.
[10] This excludes countries like Brunei, Papua New Guinea, and East Timor.
[11] This excludes jurisdictions like the British Indian Ocean Territory, or the Spratley Islands.
[12] This excludes countries like New Zealand, Madagascar, or Japan.
[13] These are Micronesia, Kiribati, the French Southern Territories, the Marshall Islands, and the Cook Islands.

Most sources in the literature relating storms to nightlights as well as most studies in development economics are based on an older yearly data source based on the Defense Meteorological Satellite Program (DMSP) of the US military (Bertinelli and Strobl, 2013). This satellite program has been followed up by NASA and the NOAA National Geophysics Data Center with the Visible Infrared Imaging Radiometer Suite (VIIRS), which 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 which had made differentiation of very light areas difficult in the older DMSP data (Mohan and Strobl, 2017). The resulting images are aggregated into monthly composites and corrected for stray light, lightning, cloud cover, and other outliers (Elvidge et al., 2017).

I then combine these globally available shapefiles[14] with geospatial data on national and regional (i.e. sub-national) boundaries of the islands in the sample. These spatial polygons are available from the Global Administrative Areas dataset.[15] Figure 2 shows the Caribbean part of the data with nightlight intensity plotted in blue. The geospatial polygons of the island economies are plotted in solid black lines for OFCs and in dashed grey lines for non-OFCs.

— Figure 3 about here —

Within each country polygon, it is then possible to calculate statistics of the nightlight intensity in each jurisdiction and each year-month available.[16] By performing such calculations for each jurisdiction and all available nightlight maps, monthly time series can be created. Here, data running from April 2012 when maps become available are created for every jurisdiction in the sample.[17] The sample has to be cut in December 2018 to observe treatment status for 1.5 years after the last observation at the time of writing (see methodological section 4.1). Figure 3 shows such series for five countries in the Caribbean and the Pacific & Indian oceans to provide intuition on the variation in this data. There is substantial variation in this data and the series drop at the same time as extreme events occur, such as hurricanes Irma & Maria in the British Virgin Island in September 2017.

[14] These large monthly nightlight maps (one month takes up around 12 Gigabite in six map fragmets) have recently been migrated to the Colorado School of Mines. Last accessed June 27, 2020, at: https://payneinstitute.mines.edu/eog/

[15] Last accessed June 27, 2020, at http://www.gadm.org/country

[16] Radiance of nightlight is measured in units of $Wcm^{-2}sr^{-1}$, or watt per steradian per square centimeter. For usability, these radiance values are 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 for most jurisdictions in the sample.

[17] The national calculations for Cuba exceeded the hardware capabilities of this author's computer, data for Cuba were therefore aggregated from Cuban regions, weighted by region size.

These data are the basis for calculating the real local impact of hurricanes. It is not prone to data gaps and of a relatively high (monthly) 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. A subnational dataset, where regional boundaries are used, is employed for robustness checks to confirm the main results for capital regions only. An R package allowing other researchers to build such data for any geospatial unit on the planet is available has already been uploaded.[18]

3.3. Mirror data on bank claims

The data availability problem in offshore finance extends to data on financial service provision. While international financial data reported by small island economies is rare, bilateral datasets allow the construction of mirror data, i.e. data reported *against* the jurisdiction of interest from other sources. In its Locational Banking Statistics, the Bank for International Settlements (BIS) provides bilateral quarterly time series on banks' international claims and liabilities on an immediate counterparty basis.

Here, mirror data on international bank claims is used.[19] These positions include loans to banks and non-bank financial institutions (NBFIs), thus capturing the funding channel of the financial sector. This dataset also includes intra-group positions. A drop in these international mirror claims indicates decreased funding requirements and thus decreased activity of the counterparty banks and NBFIs as internationally active financial service providers operate under high leverage ratios. Using the active part of the BIS data therefore captures activities of financial service providers and not passive deposits.

While coverage is not complete, the BIS makes data reported by 19 large non-OFC economies public, including mostly OECD countries.[20] While only 4 islands in the sample report any data to the BIS, reports against 26 island economies are available. These mirror claims are a second step in filling the data gap in offshore finance. These reports are summed at the counterparty country level as:

[18] It was prepared and is maintained together with Mark Toth and available at: www.github.com/JakobMie/nightlightstats.

[19] The tax evasion literature on the other hand uses data on liabilities, especially deposits, reported by tax havens themselves (see for example Johannesen and Zucman, 2014; Langenmayr, 2017; Menkhoff and Miethe, 2019). The data used in this study is from a different part of banks balance sheets and reported by different countries: it captures the active funding side of the financial sector.

[20] These reporting non-OFCs countries are: Australia, Brazil, Canada, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Italy, Japan, South Korea, Mexico, Philippines, Sweden, Taiwan, the United States, and South Africa . Luxembourg and the Netherlands are excluded due to their presence on several lists of tax havens.

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

Where country i can either be an OFC or a non-OFC island and claims are summed for all non-OFC reporting countries, $j = 1, ..., J$. A balancing choice is needed, as reports by different countries and against different counterparties start at different points in time, introducing a tradeoff between the cross sectional and time dimensions. Here, data balanced in the second quarter of 2012 is used where the satellite data becomes available. Any bilateral series that starts later is excluded in the sum above. Annex A.1 provides details and provides details and figures that indicate that the data lost is negligible in aggregate. Crucially, these mirror claims can also be constructed for islands as small as the Mauritius with 21,500 inhabitants but close to 13.5 billion USD of mirror claims reported against it in 2018:I by banks from large non-OFC.

3.4. Data on hurricanes

National data on hurricanes is taken from the EM-DAT[21] disaster database that collects the exact timing of natural disasters, including statistics on the number of inhabitants and locations affected.[22] Since such disasters are precisely dated, these data can be used at all frequencies employed here: monthly to analyze data on nightlight intensity, quarterly to analyze BIS bank claim data, and daily to analyze equity prices in the extended results. Many hurricanes in the sample hit both OFCs and non-OFCs but never all islands which provides rich treatment variation for the empirical exercises. The classification of hurricanes follows that of the Emergency Events Database.[23]

— Table 1 about here —

The resulting sample and the data introduced above is shown in Table 1. The average OFC indeed is quite small. The Cayman Islands or Bermuda have only 60,000 and 70,000 inhabitants, respectively (column 1), but mirror claims of 1,5 trillion USD and 63 billion USD (column 3). With an estimated GDP per capita of $85,700 (column 2), Bermudans are theoretically much richer than US (roughly $60,000), German ($50.000), or French ($43,000) citizens. This shows how the financial service sector inflates macroeconomic statistics. As previously noted, the nightlight mean is available for all islands (column 4). It can be used to evaluate

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

[22] The literature focusing on establishing precise growth declines due to hurricanes (see for example Strobl, 2011, 2012) provides detailed geo-spatial impact estimations of hurricanes. The present project, however, is limited by financial data that is only available nationally.

[23] This database, for example, does not classify Cyclone Gita as an emergency event in America Samoa in 2018.

hurricane impacts, the frequency of which also varies across countries (column 5). The differentiation into OFCs and non-OFCs (last column) is based on the union of the lists provided in Johannesen and Zucman (2014) and Gravelle (2015) and changed in robustness tests. Having outlined an identification strategy that allows the detection of local financial service activity as well as data that makes such investigations possible, the following section introduces the method and the main results.

4. Main Results: Hurricane Impacts

This section first introduces the empirical methodology. With two main data sources available to test hurricane impacts on small island economies, it then proceeds in two steps: first, testing for reactions of local conditions and, second, of the financial service sector. For both dimensions, results in the non-OFC sample are provided to test the identification strategy.

4.1. Methodology: Multiple Event Study with Binned Endpoints

Two particularities of the research design need to be taken into account in the empirical setup: more than one hurricane can hit an island and event-time (around a hurricane) differs from calendar time. To take both into account explicitly, an event study design with multiple treatments of the following form is employed (following Schmidheiny and Siegloch, 2020):

$$i.h.s.(y_{it}) = \sum_{t=\underline{j}}^{\bar{j}} \beta_j b_{it}^j + \mu_i + \theta_t + \varepsilon_{it} \tag{2}$$

Where $i.h.s.(y_{it})$ are the outcome variables (the inverse hyperbolic sine transformation[24] of nightlights or mirror claims in this section), μ_i are unit specific intercepts, θ_t calendar time fixed effects, and ε_{it} idiosyncratic errors. The sum around b_{it}^j collects event study dummies and binned end points such that:

$$b_{it}^j = \begin{cases} \sum_{s=-\infty}^{\underline{j}} d_{is} & if \quad j = \underline{j}; \quad lower\,bin \\ d_{i,t-j} & if \quad \underline{j} < j < \bar{j}; \quad event\,study\,dummies \\ \sum_{s=\bar{j}}^{\infty} d_{is} & if \quad j = \bar{j}; \quad upper\,bin \end{cases} \tag{3}$$

Binning the endpoints intuitively assigns observations outside the effects window $(-j : j$ in event time) to the control group, therefore improving identification of the time trend in θ_t.

[24]The log equivalent inverse hyperbolic sine transformation is calculated as $ihs(x) = log(x + (x^2 + 1)^{1/2})$. Log and level results are provided in Annex Figure A.4.5c.

Since the sample also includes islands that do not experience hurricanes during the observation window for the treatment status ($\underline{t} - \bar{j} : \bar{t} + |\underline{j}| - 1$), no further conditions on the endpoints (as pointed out in Schmidheiny and Siegloch, 2020) or the event study dummies (as pointed out in Borusyak and Jaravel, 2017) are needed for identification. Finally, $d_{i,t-j}$ collects the standard event study dummies that take value 1 j periods from the hurricane and 0 elsewhere with $d_{i,t-1}$ omitted as a baseline in the monthly data and $d_{i,t}$ in the quarterly data.[25]

The results section employs an effects window of $+/-1.5$ years of event time. The sample has to be cut before the beginning of 2019 which, at the time of writing, leaves 1.5 years of treatment observation after the effects window closes. Data on hurricanes goes back to the 50's and is available until August 2020 at the time of writing. This allows the identification of dynamic effects within the observation window $-j : j$. This three year effects window translates into $\underline{j} = -18$ to $\bar{j} = 18$ year-months for the nightlight data and $\underline{j} = -6$ to $\bar{j} = 6$ year-quarters for BIS mirror claims. Standard errors are clustered at the island level, the level of treatment variation. While this choice might seem generic, it is motivated by the unpredictability of hurricane impacts across hurricane-island pairs, following the suggestions in Abadie et al. (2017). If a hurricane actually makes landfall on a small islands can still be uncertain hours before impact. To quantify results, for ease of exposition, and to show robustness to methodological choices, conventional differences-in-differences estimations are also provided below.

4.2. The Local Impact of Hurricanes on Island Economies

This section provides the baseline impact of hurricanes on local conditions. To the best of my knowledge, no panel results on the Caribbean using VIIRS nightlight data exists to date, making the results in this section a contribution in their own right. Available studies focus on the effects on GDP of hurricanes hitting South America and the Caribbean as well as US county per capita income (Strobl, 2011). Hurricane impacts on nightlights are analyzed for the Caribbean using the aforementioned older yearly DSMP data (Bertinelli and Strobl, 2013) with one study employing VIIRS data to analyze the impact of cyclone Pam hitting Vanuatu in the Pacific Ocean (Mohan and Strobl, 2017). Assumptions about the relationship between nightlights and economic activity are not needed here, this section merely provides a baseline measure of hurricane impact. This impact can then be compared to reactions of the financial service industry.

— Figure 4 about here —

[25] This differentiation is necessary because, in quarterly data, a hurricane in the quarter preceeding impact could be up to three months away from the actual effect if it takes place at the beginning of the quarter. A quarter is classified as a hurricane quarter if least one (but sometimes more) hurricanes take place in a particular quarter. When a hurricane spans quarters, both quarters are defined as hurricane quarters.

Figure 4 shows the results of the multiple event study with binned endpoints introduced above for hurricane impacts on local conditions. The graph plots the β^j coefficients with 95% confidence intervals. The top panel provides results for the entire sample and shows a stable pre-trend for 1.5 years of event time before hurricanes hit. With the hurricane hitting at $j = 0$, a significant impact is visible. Recovery sets in immediately after that. However, it takes 5 months for the negative coefficients to be statistically insignificant and almost 9 months for coefficients to return to zero. The second and third panels now split the sample into OFCs (middle panel) and non-OFCs (bottom panel). Here, the control group is made up of never treated islands and observations that are in the binned endpoints within the same group of countries. This sample split decreases statistical power but results on both the immediate impact as well as the long recovery are confirmed.

— Table 2 about here —

To quantify results, Table 2 provides results of a differences-in-differences specifications where a treatment dummy collects the first nine months after hurricane impact. Results are robust to different cutoffs. Coefficients can therefore be interpreted as the average effect of the hurricane impact compared to the nine months before it hits. The first two columns show this regression on the log of nightlight intensity. In offshore financial centers, nightlight intensity drops by 19.4% on average for the 9 month after a hurricane hits (column 1). The effect is comparable to the non-OFC sample (18%, column 2) and statistically significant in both sub-samples. Here, the binned endpoints are shown as well and indicate that the event study is well specified with no significant results for the endpoints and coefficients on the bins close to 0. These bins are not plotted in the treatment graphs following Fuest et al. (2018). For completeness, the last three columns show the results on the inverse hyperbolic sine transformation but due to the presence of many around 0, the size of these coefficients is not straightforward to interpret here (a discussion of this issue is provided in the robustness section along with event study results for logs, ihs, and level specifications). The drop in nightlights is therefore strong on impact and the the average effect over the recovery period shows a close to 20% lower nightlight intensity on both island groups in the sample.

These impacts are in line with existing research on hurricane impacts that shows recovery periods of at least half a year and decreases of GDP growth by 0.45% to 1.5% in a given year (Bertinelli and Strobl, 2013; Mohan and Strobl, 2017; Strobl, 2011, 2012). Effects last several months with two existing studies showing an effect on nightlights that lasts 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, 2017). As a case study confirming the regression results, Annex A.2 shows the impact of hurricanes Irma and Maria in the Caribbean, the strongest hurricanes in the sample. These hurricanes are already visible by eyeballing night-light maps (Figures A.2.1 and A.2.2). Hurricanes that hit island economies are thus associated with a substantial deterioration of local conditions. These impacts are visible in both OFCs and non-OFCs and only die out nine months after impact in the OFC sample. They are consistent with qualitative evidence on power outages, evacuations, infrastructure breakdowns and general uncertainty around hurricane impacts on island economies. The next section now explores how these impacts affect the operation of the financial service sector.

4.3. The Impact of Hurricanes on Financial Service Provision

The prolonged recovery period documented above validates the use of a quarterly dataset, which is the highest frequency available from the BIS. Except for this change in frequency, results below employ the same methodology, sample choices, and treatments as the last section, and show coefficients of 1.5 years of event time before and after hurricane impacts. Contrary to the strong impacts on local conditions, the top panels of Figure 5 shows a striking non-result in the financial sector on offshore financial centers. BIS mirror claims reported against OFCs do not react to hurricanes at all. The pre-trend between affected and non-affected OFCs quite stable for macroeconomic data on international capital movements. The post-hurricane coefficients are virtually zero for 1.5 years and never statistically significant. Over three entire years of event time around hurricane impacts, no significant effect is visible.

— Figure 5 about here —

These results could show that the financial service sector is not affected by hurricanes in general. This is not the case. The bottom panel of Figure 5 shows the results of the same regression for the non-OFC part of the sample, the falsification exercise. As for OFCs, the pre-trend is statistically insignificant and coefficients are small. When the hurricane hits, however, mirror claims start to deteriorate. The drop builds up over time since mirror claims are a stock measure. In the first quarter after the hurricane hits, mirror claims reported against affected OFCs decrease by 17.6% relative to the control group. By then end off the effects window, this drop increases to 36% compared to the first quarter of the hurricane impact. Since mirror claims capture the international lending channel for banks and non-bank financial institutions, the fact that the customer base of banks on OFCs and non-OFCs differs is not crucial here: No matter what activity the local financial actor carries out, its day-to-day operations depend on foreign (including intra-group) funding. Only international positions are measured here, making data comparable across island types irrespective of how the financial sector then uses this funding.

— Table 3 about here —

To make results more interpretable quantitatively, Table 3 shows differences-in-differences exercises. Here, the six treatment lags in the effects window are collected into one dummy and should be interpreted relative to the pre-event window. Column 1 shows the insignificant effect in the OFC sample. Again, the binned endpoints are also plotted here and are not significant, again with coefficients close to 0. Column 2 shows the non-OFC sample. The average effect in the post-event period indicates a 33.6% reduction in mirror claims relative to the pre-event window. The upper bin ($\text{Bin}_{j=6:j=\bar{j}}$) remains significantly negative which indicates a persistent effect. This is intuitive for a stock measure. A transitory shock to the competitiveness of non-OFC banks and NBFIs reduces this measure long term unless affected islands start to *outperform* the control group in later periods. Such catching up is only visible partially as the long term effect is about half the size of the short term impact (17.4%). To show the difference between reactions of OFCs and non-OFCs directly, column 3 uses the entire sample with an OFC interaction term on the hurricane dummy. Intuitively, this pools the control group of both sub-samples. The post-hurricane dummy interacted with the OFC dummy shows insignificant and small coefficients while coefficient on the interaction term with the non-OFC dummy again shows a large negative and statistically significant effect.

To verify that the results above are not driven by developments in the banking sector that are independent of hurricanes, columns 4 and 5 carry out another falsification exercise. On top of the active side of non-OFC banks' balance sheets that were used so far, the BIS also provides data on the passive side. These positions measure the amount of liabilities, mostly bank deposits, that are reported against islands in the sample. Such mirror-liabilities include, for example, the bank account of a Jamaican company at a bank in France. These positions do not need to be reduced when a hurricane hits because reporting banks are not hit by the hurricane. Results show small coefficients both for the OFC and non-OFC depositors. The small positive coefficent on depositors from OFCs (column 4) is marginally significant, however, the robustness section shows that it should not be interpreted. These result do not mirror the effects on mirror claims reported above. This shows that the significant negative effect on mirror claims in non-OFCs (column 2) is no statistical artifact of other bank sector developments.

All in all, the results of this section show pronounced hurricane effects on local conditions as well as on the financial sector in non-OFCs. The only area where hurricanes did not appear to take place in the event studies is financial service provision on offshore financial centers. There is a disconnect between local conditions and international financial service activity on OFCs in reactions to local shocks. These results are robust over a large number of robustness checks that are reported in section 6 further below. If, indeed, local baking or legal skills are useful for international customers, it is puzzling that these activities go on unabated during hurricanes. Instead, these results are consistent with the hypothesis that international financial activity that is booked as taking place in OFCs is not, in fact, local.

5. Extended Results

This section provides three sets of extended results. First, the effects visible in the BIS data are confirmed with a different approach and data-source looking at investors of banks and non-bank financial institutions on the islands in the sample. Second, descriptive evidence is provided that gives an indication about where activity might be actually taking place by showing that local incorporation activity on island OFCs decreases during public holidays in Tokyo, New York, and London. The third section finally shows a missing relationship between financial service provision and local conditions in general, but only on OFCs. This casts doubt on offshore finance as a long term development strategy for small island economies.

5.1. Reactions of International Investors

Bank and non-bank financial institutions are integrated internationally. Of those domiciled in islands in the sample, a number are listed on international stock exchanges, making it possible to test for market reactions to hurricanes. I construct a daily dataset of 395 equity price series taken from Bloomberg for a sample period starting on the first of April 2012 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.

As common in analyses of financial markets, I carry out an event study in the spirit of Kothari and Warner (2007) using hurricanes as a potential shock to the net present value of the equity of banks and NBFIs domiciled in OFCs. First, returns below the 1st percentile and above the 99th percentile are windsorized, then daily abnormal returns (AR_{it}) are calculated 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).

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

In equation 4, i denotes the 395 equity price series and t the respective day. As mentioned above, hurricanes are hard to anticipate and especially the extent of the impact comes as a surprise. Forward looking investors will therefore adjust their portfolio quickly if the business they are invested in experiences a detrimental shock. A treatment window of 1.5 years is therefore not useful here. Instead, I follow Johannesen and Larsen (2016), and 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, interpreted as the response of investors to unexpected hurricane impacts. For statistical inference, both a simple t-test and the ratio of post-event cumulative abnormal return over the pre-event standard deviation of abnormal returns are used (Kothari and Warner, 2007).

— Table 4 about here —

Table 4 shows the results. The top panel shows the naïve specification outlined above. While cumulative abnormal returns are negative for OFCs, statistical significance is not visible for either of the two tests; conventional critical values are far off. As before, the reaction of non-OFCs is provided as a benchmark showing that in a non-OFC sample, reactions are highly significant and pronounced. The middle panel reduces the panel to equity issuers with names that indicate banks, holding companies or NBFIs[26] and the bottom panel changes the windsorizing to 5% of returns. Results are consistent across specifications.

On average, foreign investors do not seem to perceive the strong exogenous shock visible in local conditions as detrimental to their portfolio of OFC bank and NBFI stock. Again, this

[26] The precise terms used for the string search are the following: I identify banks ("bank", "banco", "bancorp", "scotia", and "sagicor group"), holdings ("holding"), and NBFIs ("insurance", "capital investor", "investment", "financial", "finance", "financiero", "fund", "trading", "financial services", "trust", "inversiones", and "credit".)

result is especially striking when compared against the strong drop in returns in non-OFCs. It does, however, confirm the main results on international bank claims and is consistent with the interpretation that international financial activity on OFCs does not take place locally and that international investors are well informed about this fact. Taken together, these results raise the question where it actually takes place. The following section provides an indication.

5.2. Local Company Incorporations

Corporate registries of OFCs are generally not publicly available, indeed, secrecy is part of the OFC definition used here. However, in February 2018, the international consortium of investigative journalists (ICIJ) published significant subsets of the leaked corporate registries of Aruba, the Cook Islands, Bahamas, Barbados, Malta, Nevis, and Samoa. Without the Appleby data, that made headline news but is not representative for a specific jurisdiction, the leaked registries include data on 265,150 unique company registrations and their incorporation dates. For the six OFCs for which company registers were leaked, I aggregate these incorporation dates into time series counting the number of incorporations per day on the island in question. While this sample is to small to analyze hurricane impacts statistically, its daily dimension shows interesting patterns across work days.

— Figures 6 and 7 about here —

As a sanity check, Figure 6 shows incorporation activity over the entire sample by weekday in the six islands. The fact that almost no incorporations take place on weekends suggests some connection to actual human activity. If activity declines during weekends, it is reasonable to assume that it declines during public holidays as well. The interesting question is: During whose public holidays?

A decline in corporation activity during local public holidays is clearly visible in the data, using data on all public holidays on these OFCs since 1990 (see Annex A.3). Figure 7 now shows the difference in daily incorporations on public holidays in the financial centers London, Tokyo, and New York that are normal workdays on the islands in question. The baseline against which these incorporations are compared excludes weekends and public holidays on the OFCs from the sample. These effect are therefore a lower bound: common holidays such as New Year's Eve and Christmas are also local holidays and excluded here. Nevertheless, almost all differences are negative. During a public holiday in London that is a normal workday on St. Kitts and Nevis, incorporation activity on St. Kitts and Nevis still drop by 4.5 incorporations (left panel) or 50% of average daily workday incorporation activity (right panel). Barbados, the Cook Islands, and Malta also show drops of around 20%. Financial service activity in

OFCs is connected to activity elsewhere, but human work days do still matter. This evidence is selective since only six time series on incorporations are available. Still, it hints at an interesting avenue for future research investigating the bilateral links between OFCs and financial centers in OECD countries. As seen here, the three cities shown in Figure 7 are valid starting points.

5.3. Offshore Finance and Long Term Development

If financial service activity is not local, the question arises if the OFC actually gains much on aggregate by allowing such activity to be booked within its jurisdiction. The large financial positions in OFCs could lead to high income in the form of fees or taxes. Such income can be substantial, even with very low tax rates due to the inflated foreign tax base relative to small island economies (see Tørsløv et al., 2020; Zucman, 2013, for a similar point regarding European tax havens). However, it is an open question how these funds are used and to what extent they, or generated revenues, end up in the local economy. By investigating the direct relationship of nightlights and mirrorclaims, a result is borrowed from development economics, namely, that nightlight intensity is positively correlated with measures of economic development (Donaldson and Storeygard, 2016; Henderson et al., 2012).

— Figure 8 about here —

Using both series at quarterly frequency by averaging nightlight intensity over the quarter, Figure 8 plots nightlights over international bank mirror claims for each year-quarter and country. Both variables are again transformed using the log-equivalent inverse hyperbolic sine transformation to retain negative and zero observations. An equivalent of Figure 8 using logs is provided in Annex Figure A.3.2. The top panel of Figure 8 shows that there is no relationship between local conditions and international bank claims in the OFC part of the sample, 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. The bottom panel shows a positive correlation for non-OFCs both between countries as well as within countries. This relationship is not linear but increases over mirror claims. If nightlights do proxy real economic activity, this image is intuitive: For countries not dominated by offshore finance, higher foreign capital positions are associated with higher local economic activity. The missing link in OFCs on the other hand raises the question if offshore finance actually supports the aggregate development of small island economies.

6. Robustness Checks

This section summarizes tests that show the robustness of the main results. Details are provided in Annex A.4. They are organized along three themes: First, sample robustness is tested, second, robustness to different OFC classifications is tested for the mirror claims results where both groups differ and third, tests changing the methodological choices are provided. Results are robust across these specifications.

Sample robustness: To show that the results are not driven by a particular country in the sample, an extensive sample check is provided here. For both island groups and both outcome variables of the main results, specifications that drop each sample country in turn are provided. Figure 9 shows the results for nightlights. The OFC part of the sample is plotted in the top panel and shows that results do not fluctuate much. The bottom panel shows the results for the non-OFC part of the sample where results are also robust across all specifications. Not a single specification deviates significantly from the main results.

— Figures 9 and 10 about here —

Figure 9 plots results of the same exercise for mirror claims. The top panel again shows the OFC part of the sample where not a single coefficient turns significant and coefficients are quite stable around 0. These results also re-enforce the interpretation of this estimation as a non result: Coefficients are small, insignificant, and do not exhibit sign certainty. The bottom panel plots the same results for the non-OFC part of the sample. Results hold here as well. Generally, despite the limited availability of island economies, results are very robust to changes in the sample specification.

OFC classifications: Another potential concern with the main specification at hand is the classification of islands into OFCs and non-OFCs for the differing impact on financial service activity. Results so far use the union of OFCs in Gravelle (2015) and Johannesen and Zucman (2014), Table 5 uses three different tax haven lists. As before, the hurricane dummy in these differences-in-differences specifications collects the six post-event dummies. Coefficients can therefore be quantitatively interpreted as the percentage drop in mirror-claims compared to the six year-quarters before the hurricane. The first three columns show the OFC part of the sample, columns 4-6 the non-OFC part. Columns 1 and 4 show the effects of employing the tax haven list in Gravelle (2015). Columns 2 and 5 move to the tax haven list of Johannesen and Zucman (2014) and columns 3 and 6 to the older list of Hines and Rice (1994).

— Table 5 about here —

Results hold without qualifications for the first two lists. Only the last specification (non-OFCs using the older tax haven list) shows that the sample is not cleanly separated anymore. Although the main results still hold here. This is due to the fact that the Hines and Rice (1994) list was created 18 years before the sample in this study starts. At that time, many small island tax havens were not on the radar of policy makers and economists or did not engage in OFC activities yet. This list thus moves Aruba, Mauritius, Nauru, Niue, Samoa, Trinidad & Tobago, and the U.S. Virgin Islands into the non-haven part of the sample. In a sample starting in the second quarter 2012 when Maritius for example was a major origin of international foreign direct investment into India and Africa, such a change should actually affect the results. While many more lists are available in the literature, they do not change the assignment in the sample at hand compared to the ones employed above. For example, the lists of Dharmapala (2008), Gravelle (2015), and OECD (2000) all categorize the same islands in the sample as OFCs, although they differ for other countries. A version of this table without binned endpoints is provided in the Annex (Table A.4.1) and confirms the results.

Methodological Choices: Pure differences-in-differences versions of the main tables without binned endpoints are provided in Tables A.4.2 and A.4.3 and confirm the results of the tables provided in the main results with the exception of the slight positive effect of the falsification exercise on liabilities which turns insignificant. The Annex also provides pure event study specifications of the falsification exercise separately for OFCs and non-OFCs (Figure A.4.1). They confirm the non-result discussed in the main section with one noteworthy add-on: the post event dummies of the slight positive effect visible in the falsification exercise fluctuate more and, if anything, show a general positive trend over the effects window. Again, this leads to the conclusion that this effect should not be interpreted. Finally, to show the issue of numerical values around 0, Figure A.4.3 in the Annex plots the distribution of all nightlights in the sample. It shows a large number of small observations close to 0 which biases coefficients using the the inverse hyperbolic sine transformation downwards. To show that this does not effect the interpretation of the event studies, Figure A.4.5c shows event study specifications for nightlights using the log, the inverse hyperbolic sine, and the level of nightlight intensity. In all of these cases, hurricane impacts are clearly visible. This confirms that, beyond the difficulties in interpreting coefficents of variables with many observations around 0, this methodological choice is not crucial for the results presented here. The main text therefore uses the more common log specification to interpret effect sizes.

7. Conclusions

Little reliable empirical evidence is available on activities of the financial service sector in Offshore Financial Centers (OFCs). While a quickly growing literature studies the customers of OFC financial services, such as tax evading individuals, profit shifting firms, or corrupt politicians, the financial intermediaries that facilitate such activities have been largely overlooked. Indeed, policy measures are introduced implicitly following the claim that financial services are provided locally on OFCs. I show that it is unlikely that financial services booked through OFCs are actually carried out locally and provide a number of extended results outlining the implications.

I exploit the natural experiment of re-occurring hurricanes and typhoons in the Caribbean and the Pacific to determine if financial activity registered to OFCs is physically taking place there. A first set of results shows significant hurricane impacts of close to 20% on local conditions proxied with satellite data on nightlight intensity. These effects take 9 months to disappear and are observable for both OFCs and non-OFCs. They are robust to different samples, OFC lists, and methodological approaches.

However, when investigating data measuring international bank claims against banks and non-bank financial institutions in OFCs, no reactions are visible. International financial activity seems to continue unabated, with no significant effects in either direction and coefficients close to zero. To potentially falsify the identifications strategy, reactions of non-OFCs are investigated, which do show significant drops in bank claims reported against them. These results are again robust across a large number of specifications. In extended results, these effects are confirmed by showing that international investors react similarly. Equity of banks and non-bank financial institutions domiciled in OFCs and traded on international stock exchanges do not experience significant negative abnormal returns after hurricanes hit. These results are consistent with no local presence of financial service firms on OFCs large enough to be visible in aggregated data.

To inform about the actual location of financial service providers, I provide indicative evidence based on leaked datasets. The number of daily incorporations on six OFCs for which corporate registries were leaked shows that local incorporation activity declines during public holidays in Tokyo, London, and New York that are normal workdays on the island in question. These results beg the question if the OFC actually profits from offshore finance if it is booked from elsewhere. In another set of extended results, I document an absence of a direct link between nightlight intensity and international bank claims for OFCs islands. Both are, however, positively correlated both within and between non-OFC islands. This casts doubt on offshore finance as a valid development strategy for small island economies.

Beyond providing first evidence on the (non-)activity of financial intermediaries on OFCs, this study provides a number of auxiliary contributions. I show that identification strategies beyond the usual tax changes or policy measures targeted at tax evasion or profit shifting are feasible to study offshore finance. I also introduce and construct several novel datasets measuring local conditions and the performance of the financial service sector on small islands jurisdictions including OFCs. Third, I contribute to open science since an R package allowing the construction of different nightlight datasets has been made available online. Finally, it shows that the assumption of no significant activity on OFCs can most likely be extended to the financial sector.

Several important policy conclusions arise from the evidence provided here. First, current regulation attempts could be mistargeted by focusing on the OFC as the collector of information. If financial service activity is not carried out locally, even a compliant OFC would have no possibility to enforce reporting requirements or combat fraud with audits or by searching the premises of an institution. Well informed financial service providers could be aware of this as well. This could explain part of the mixed success of such regulation attempts (Bustos et al., 2020; Johannesen, 2014; Johannesen and Zucman, 2014; Menkhoff and Miethe, 2019). Second, the results raise financial stability concerns. Potential risks created in non-OFCs could be underappreciated if they exclude the activity that is booked through OFCs but actually carried out in non-OFCs. Third, the results here cast doubt on offshore finance as a valid development strategy for small island economies.

This study hopefully provides a useful starting point for future research into how international financial flows are organized. The data, identification strategy, and methodology all lend themselves to further analysis. Future research should focus on establishing the bilateral links between specific OFCs and financial centers such as London, Tokyo and New York in more depth and continue to expand data availability for financial service activity on OFCs. Evaluations of policy initiatives attempting to regulate OFCs should take into account that the OFC itself might not be able to enforce access to the activities it is supposed to report on. The development implications of the results presented here raise the question which alternative development strategies are available to small island economies in the face of increasing natural shocks of which hurricanes are only one. Finally, future research should repeat the significant progress made in the analysis of the customers of offshore finance, such as profit shifting firms or tax evading individuals, in the analysis of the financial intermediaries that facilitate their international strategies.

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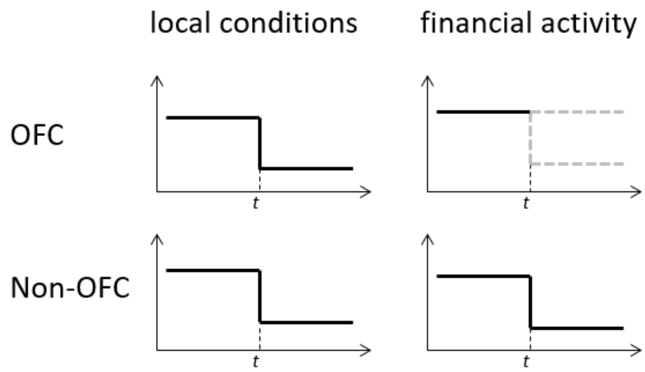
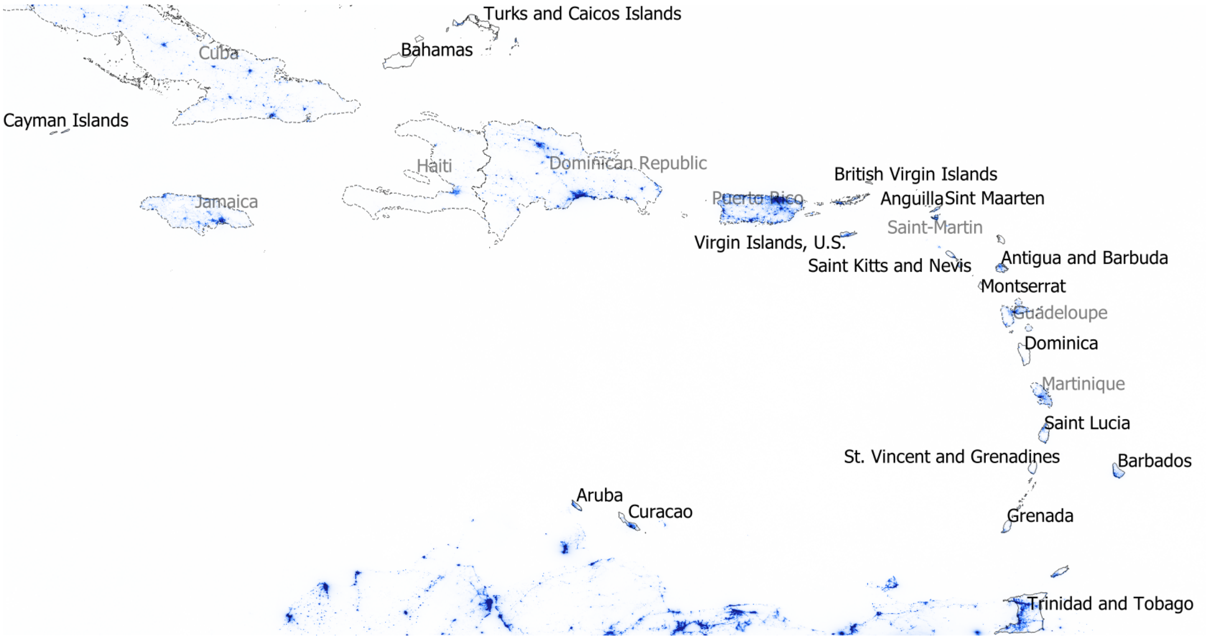
Tables and Figures

Figure 1: Schematic reactions to hurricane impacts



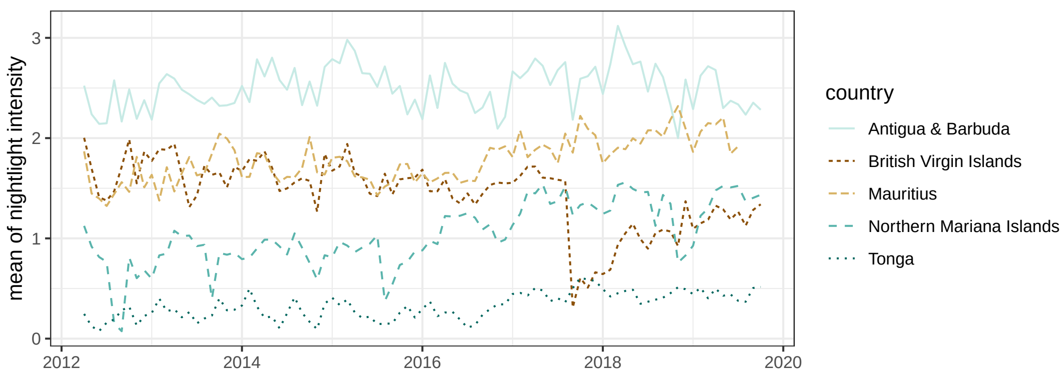
Notes: Hypothetical reactions to hurricane impact at time t on the horizontal axis for offshore financial centers (top panel (OFCs, top panel) and non-OFCs (bottom panel).

Figure 2: Nightlights and jurisdictions in the Caribbean



Notes: Shows VIIRS nightlights and administrative boundaries of Caribbean island economies. Offshore financial centers are shown with black labels and solid boundaries, non-OFCs with grey labels and dashed lines. Blue areas without borders are northern areas of South America. Radiance of nightlight is measured in units of $Wcm^{-2}sr^{-1}$, or watt per steradian per square centimeter multiplied by $1E9$. Data sources: NASA, GADM, NOAA.

Figure 3: Monthly nightlight intensity for selected jurisdictions



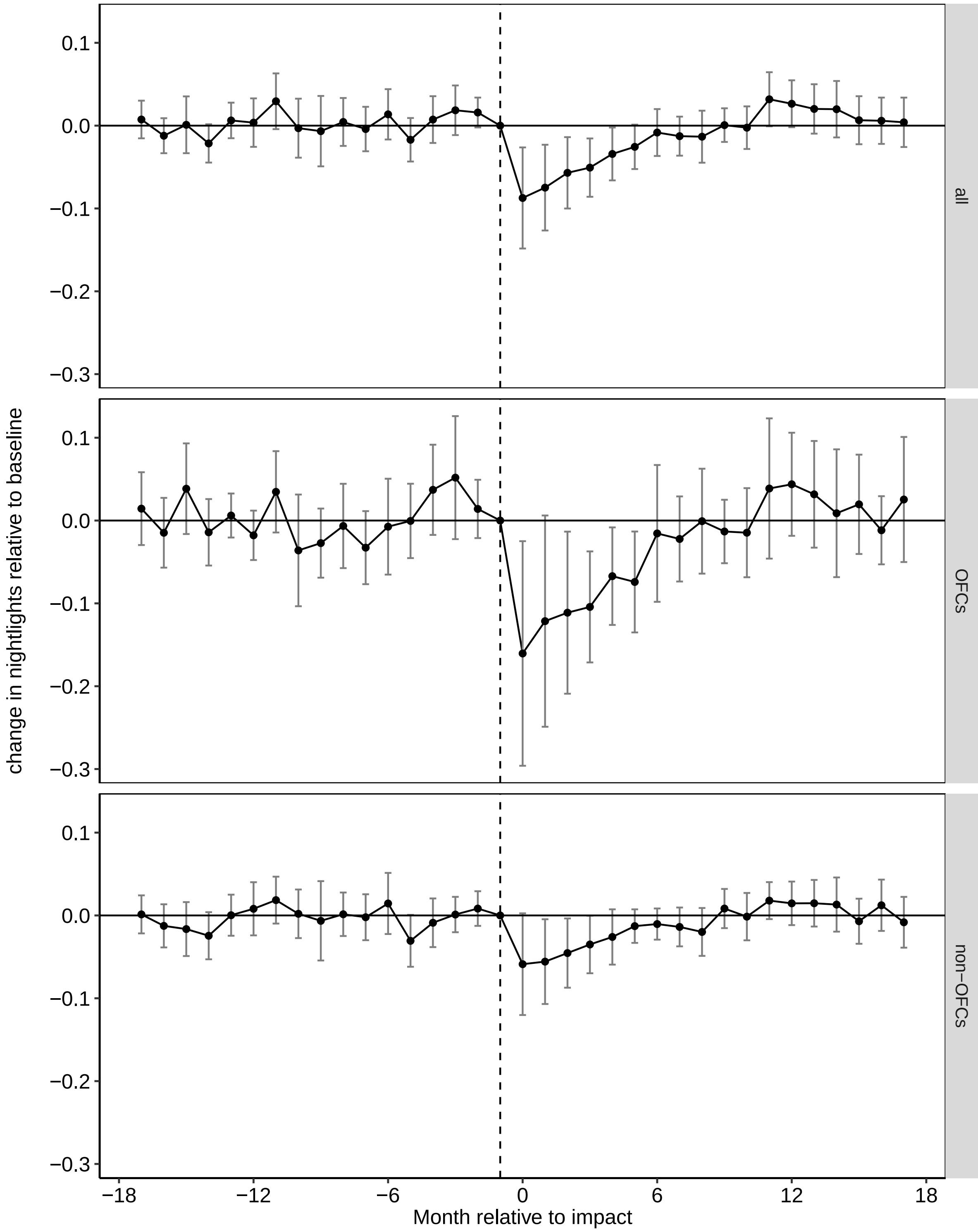
Notes: Shows time series of the mean of VIIRS nightlights starting in April 2012 when Data becomes available for selected countries in the Caribbean and the Pacific & Indian oceans. The series show the mean of nightlight intensity (vertical axis) plotted over the year-month where the images were taken (horizontal axis). Data sources: NASA, GADM, NOAA, authors calculations.

Table 1: Sample of island economies

	population	GDP p.C.	mirror claims 2018:I	mean(light)	hurricanes after 2012:II	OFC
	(1)	(2)	(3)	(4)	(5)	(6)
American Samoa	49,437	11,200		1.444	0	0
Anguilla	17,087	12,200		3.039	1	1
Antigua & Barbuda	94,731	26,300		2.500	1	1
Aruba	115,120	25,300	0.384	6.038	0	1
Bahamas	329,988	25,100	57.480	0.559	6	1
Barbados	293,131	18,600	20.580	4.577	1	1
Bermuda	70,864	85,700	65.970	6.510	0	1
British Virgin Islands	35,015	42,300		1.439	1	1
Caribbean Netherlands	26,220			1.020	0	0
Cayman Islands	58,441	43,800	1,602.000	4.813	0	1
Christmas Island	2,205			0.530	0	0
Cocos (Keeling) Islands	596			0.174	0	0
Comoros	846,281	1,600	0.014	0.116	2	0
Cuba	11,059,062	12,300	0.538	0.447	8	0
Curaçao	149,648	15,000	17.470	6.166	0	1
Dominica	73,897	12,000	0.033	0.337	2	1
Dominican Republic	10,734,247	17,000	2.545	0.890	7	0
Fiji	920,938	9,900	0.376	0.138	4	0
Grenada	111,724	14,700	0.008	1.222	0	1
Guadeloupe	397,990			2.610	1	0
Guam	167,772	35,600		4.829	0	0
Haiti	10,646,714	1,800	0.197	0.189	7	0
Jamaica	2,990,561	9,200	0.814	1.287	4	0
Maldives	391,904	18,600	0.165	1.806	0	1
Martinique	380,877	27,305		3.718	1	0
Mauritius	1,379,365	21,500	13.510	1.782	1	1
Mayotte	272,730			1.449	0	0
Montserrat	5,292	8,500		0.289	0	1
Nauru	11,359	12,200	0.0005	3.426	0	1
New Caledonia	279,070	31,100	5.309	0.212	0	0
Niue	2,000			0.090	0	1
Norfolk Island	1,748			0.108	0	0
Northern Mariana Islands	51,994	24,500		1.051	2	0
Palau	21,516	14,700		0.220	2	0
Pitcairn Islands	50			0.099	0	0
Puerto Rico	3,351,827	37,900		4.470	3	0
Réunion	895,231			1.997	2	0
Saint Martin (French part)	32,556			5.499	1	0
Samoa	203,774	5,700	4.172	0.114	2	1
Seychelles	95,981	27,800	2.154	0.691	1	1
Sint Maarten	43,847	66,800		12.520	1	1
Solomon Islands	647,581	2,200	0.052	0.049	3	0
Sri Lanka	22,889,201	12,600	1.767	0.396	3	0
St. Barthélemy	7,122			2.354	1	0
St. Kitts & Nevis	52,715	26,800		2.293	1	1
St. Lucia	164,994	26,800	0.026	1.877	1	1
St. Vincent & Grenadines	102,089	11,600	0.409	0.783	1	1
Taiwan	23,603,049	49,100	53.010	4.385	8	0
Tokelau	1,647			0.039	0	0
Tonga	106,095	5,900	0.028	0.332	4	1
Trinidad & Tobago	1,218,208	31,200	1.266	6.254	0	1
Turks & Caicos Islands	52,570	29,100	0.197	0.730	1	1
Tuvalu	11,052	3,700		0.152	1	0
U.S. Virgin Islands	107,268	36,100		5.670	1	1
Vanuatu	288,037	2,700	0.132	0.333	3	1
Wallis & Futuna	15,854		0.026	0.132	1	0

Notes: Shows data on island economies in the Caribbean and the Pacific & Indian Oceans. Population and GDP per capita are taken from the CIA World Factbook estimates (Jul. 2017, where available). Column 3 shows the sum of international claims (in billion USD) reported on sample islands by non-OFCs that provide data to the BIS locational banking statistics in 2012:II or earlier. Column 4 shows means of nightlight intensity over the sample period. Column 5 shows the number of hurricanes after 2012:II and column 6 finally indicates if the jurisdiction is classified as an OFC or not based on the unions of the lists in Johannesen and Zucman (2014) and Gravelle (2015).

Figure 4: Hurricane impacts on nightlights



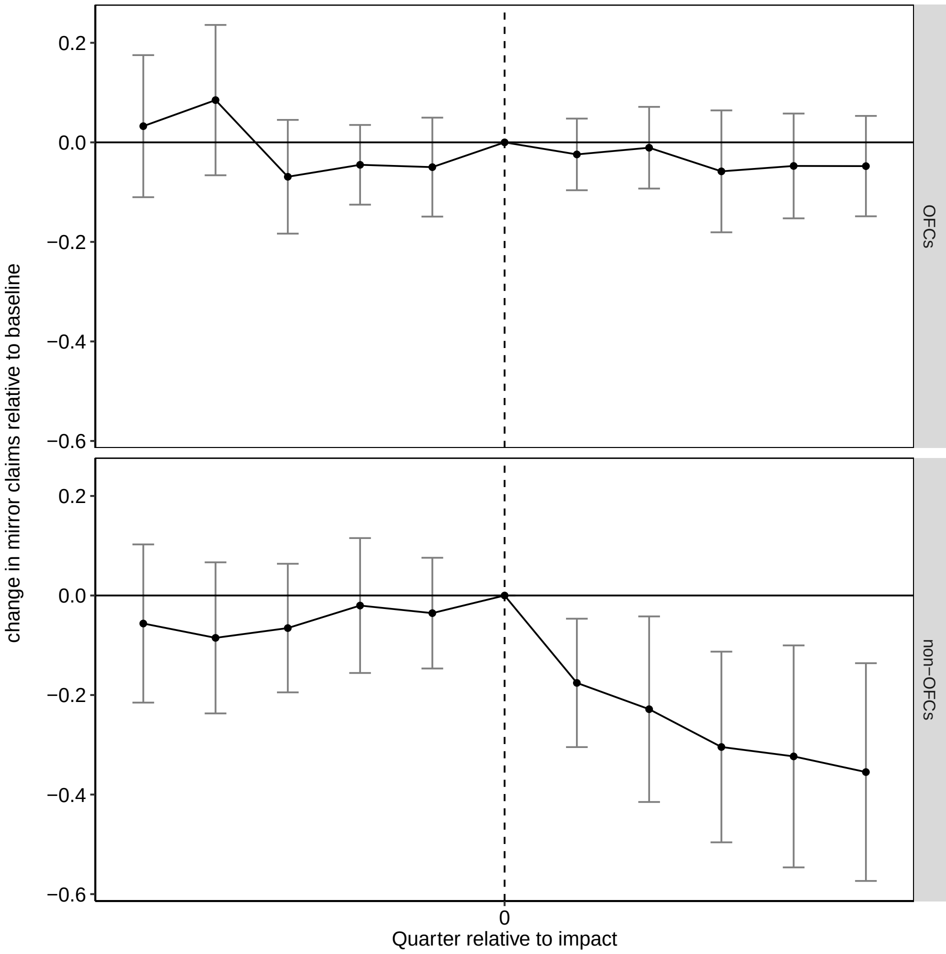
Notes: Plots coefficients of the multiple event study with binned endpoints outlined in the main text for monthly data. The estimation takes the following form: $i.h.s.(y_{it}) = \sum_{t=\underline{j}}^{\bar{j}} \beta_j b_{it}^j + \mu_i + \theta_t + \varepsilon_{it}$, notation being identical to the main text and b_{it}^j collecting event study dummies as well as binned endpoints. The top panel shows the entire sample, the second and third panels split this sample into OFC and non-OFC islands respectively. The baseline dummy left out of the regression is the month before the hurricane ($j = -1$) and 95% confidence intervals are plotted in grey, based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

Table 2: Quantifying nightlight impacts

	Dependent variable:			
	log(nightlight intensity)		i.h.s.(nightlight intensity)	
	OFCs	non-OFCs	OFCs	non-OFCs
	(1)	(2)	(3)	(4)
$\text{hurricane}_{j=0:j=8}$	-0.194^{***}	-0.180^{***}	-0.098^{**}	-0.073^{***}
	(0.068)	(0.068)	(0.041)	(0.028)
$\text{Bin}_{j=9:j=\bar{j}}$	0.003	0.067	0.014	-0.005
	(0.049)	(0.041)	(0.017)	(0.007)
$\text{Bin}_{j=\underline{j}:j=-9}$	0.081	0.049	0.023	0.005
	(0.055)	(0.048)	(0.021)	(0.006)
country f.e.	Yes	Yes	Yes	Yes
year-qtr f.e.	Yes	Yes	Yes	Yes
Observations	2,145	2,189	2,187	2,349
R^2	0.172	0.280	0.175	0.279

Notes: Shows results of a difference in difference exercise with a dummy ($\text{hurricane}_{j=0:j=9}$) taking value 1 if there was a hurricane in the last nine year-months. Results are reported split-sample, first showing the OFC part of the sample, then the non-OFC part of the sample. Columns 1 and 2 show results using the log of nightlight intensity, colums 3 and 4 using the inverse hyperbolic sine transformations. *p<0.1; **p<0.05; ***p<0.01 based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

Figure 5: Hurricane impacts on the financial sector



Notes: Plots coefficients of the multiple event study with binned endpoints outlined in the main text for quarterly data. The estimation takes the following form: $i.h.s.(y_{it}) = \sum_{t=\underline{j}}^{\bar{j}} \beta_j b_{it}^j + \mu_i + \theta_t + \varepsilon_{it}$, notation being identical to the main text and b_{it}^j collecting event study dummies as well as binned endpoints. The baseline dummy left out of the regression is the quarter of the hurricane ($j = 0$) and 95% confidence intervals are plotted in grey, based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level. The top panel plots the OFC part of the sample, the bottom part the non-OFC part of the sample.

Table 3: Further results using BIS data

dependent var.:	mirror claims			mirror liabilities	
sample:	OFCs (1)	non-OFCs (2)	all (3)	OFCs (4)	non-OFCs (5)
$\text{hurricane}_{j=1:j=6}$	0.006	-0.336^{***}		0.125^{*}	0.086
	(0.057)	(0.083)		(0.075)	(0.064)
$\text{hurricane}_{j=1:j=6}\times$ OFC			-0.077		
			(0.076)		
$\text{hurricane}_{j=1:j=6}\times$ non-OFC			-0.210^{**}		
			(0.087)		
$\text{Bin}_{j=\underline{j}:j=-6}$	0.056	-0.098	-0.066	0.161	0.031
	(0.086)	(0.082)	(0.055)	(0.107)	(0.050)
$\text{Bin}_{j=6:j=\bar{j}}$	-0.072	-0.174^{**}	-0.074	0.088	0.056
	(0.077)	(0.078)	(0.066)	(0.067)	(0.045)
country f.e.	Yes	Yes	Yes	Yes	Yes
year-qtr f.e.	Yes	Yes	Yes	Yes	Yes
Observations	548	317	865	548	344
R^2	0.243	0.212	0.132	0.061	0.098

Notes: Shows results of a difference in difference exercise with a dummy ($\text{hurricane}_{j=1:j=6}$) taking value 1 if there was a hurricane in the last six year-quarters. Columns 1 to 3 show results on mirror claims for OFCs (1) and non-OFCs (2), as well as the entire sample (3) with an interaction term. Columns 4 and 5 report a falsification exercise showing results on all liabilities reported against islands in the sample. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

Table 4: Cumulative average abnormal returns after hurricanes

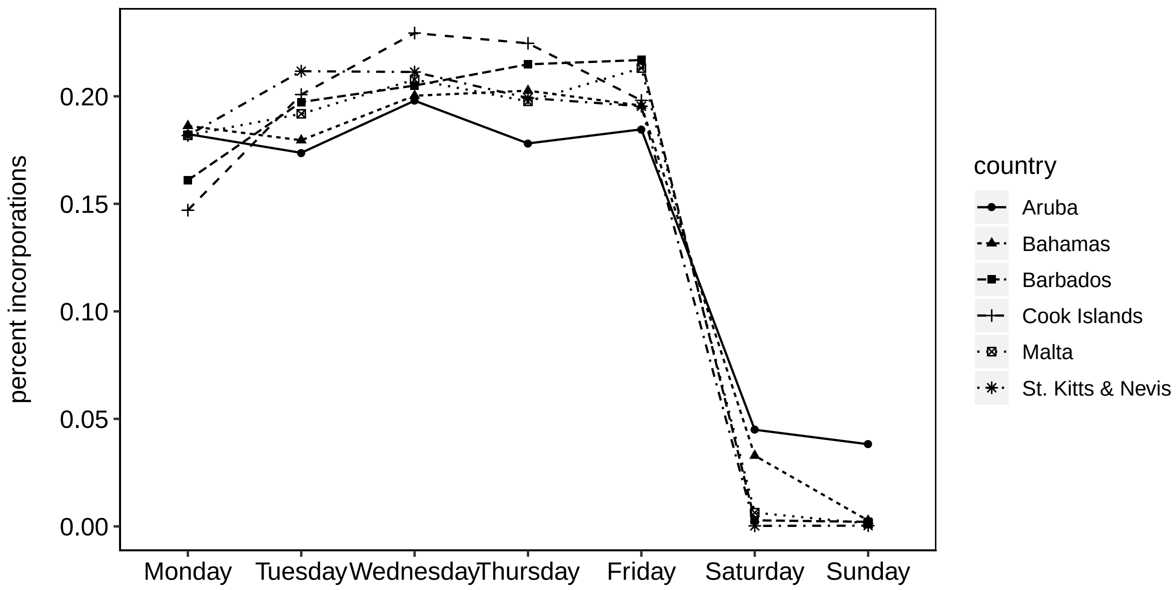
naïve	domiciled in OFCs	domiciled in non-OFC
CAARs (k=0 : k+3)	-0.556	-1.076***
t-statistic	(1.195)	(3.014)
Kothari Warner (2 7) statistic	(-0.674)	(-3.311)

refined string search	domiciled in OFCs	domiciled in non-OFC
CAARs (k=0 : k+3)	-0.930	-1.521***
t-statistic	(1.549)	(3.194)
Kothari Warner (2 7) statistic	(-1.127)	(-3.527)

drop 5% and 95% outliers	domiciled in OFCs	domiciled in non-OFC
CAARs (k=0 : k+3)	-0.973	-1.615***
t-statistic	(1.339)	(3.708)
Kothari Warner (2 7) statistic	(-1.107)	(-9.475)

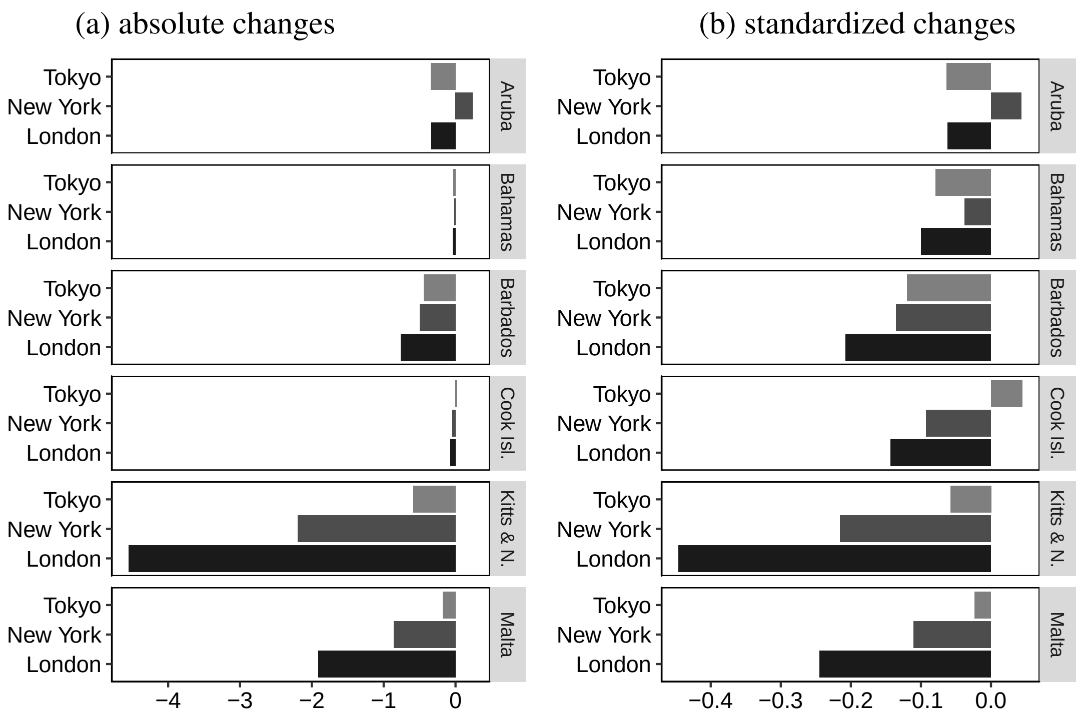
Notes: Shows results of the Kothari and Warner (2007) event study specification. The top panel provides the naive event study with cumulative abnormal returns of equity of companies domiciled in OFCs shown in column 1. Column 2 shows the non-OFC sample. The middle panel refines the string search to banks and non-bank financial institutions and the bottom panel changes the windsorizing from 1% to 5% of outliers. *p<0.1; **p<0.05; ***p<0.01

Figure 6: Incorporations per weekday



Notes: Shows percentage of daily incorporations by weekday for the six OFCs for which corporate registries were leaked

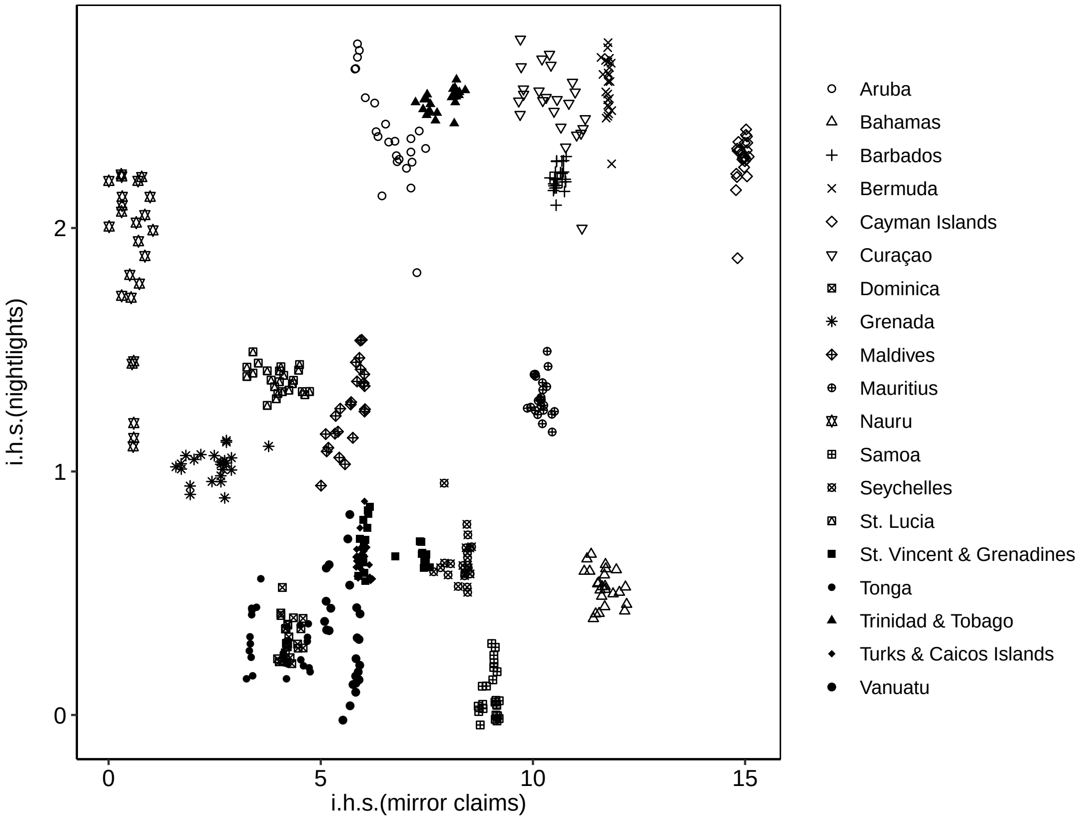
Figure 7: Changes in incorporations on foreign public holidays



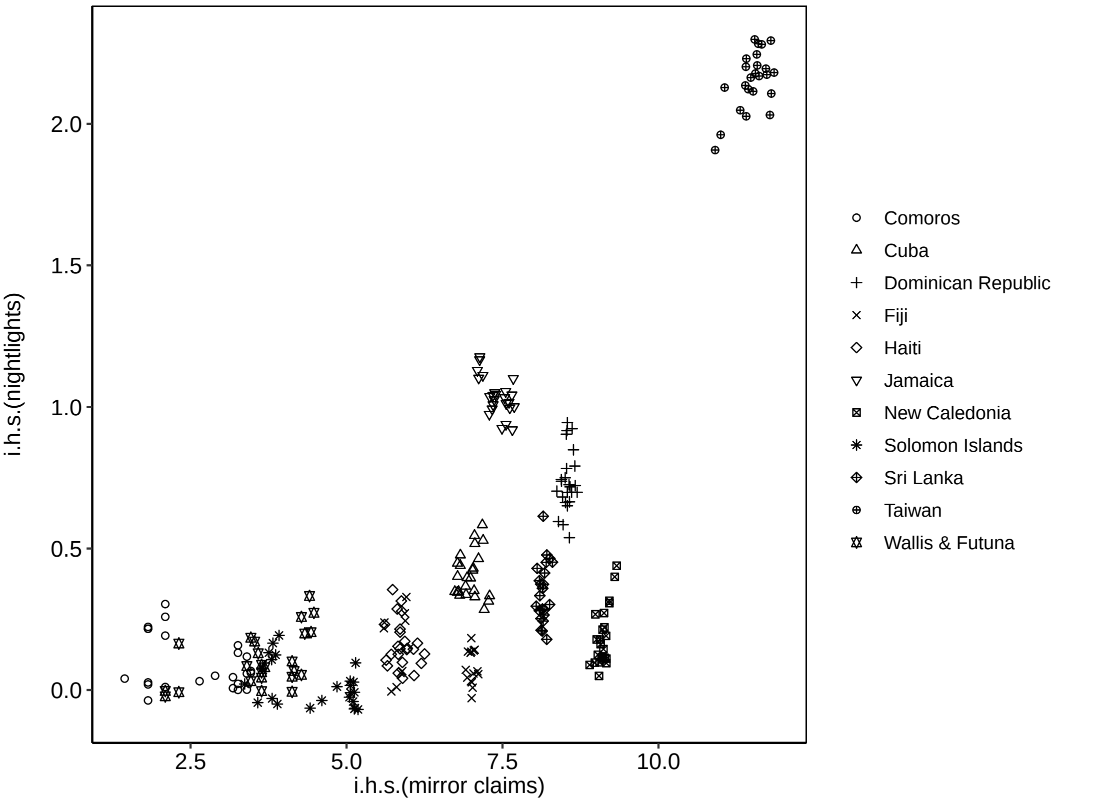
Notes: Shows absolute (panel a) and standardized (panel b) changes in incorporations relative to the average incorporation activity excluding weekends and local holidays. Data on public holidays is publicly available and used starting with 1990. Foreign holidays are public holidays in London, New York, and Tokyo that are normal workdays on the six islands plotted.

Figure 8: Direct correlations of nightlights and mirror claims

(a) OFC sample: no correlation



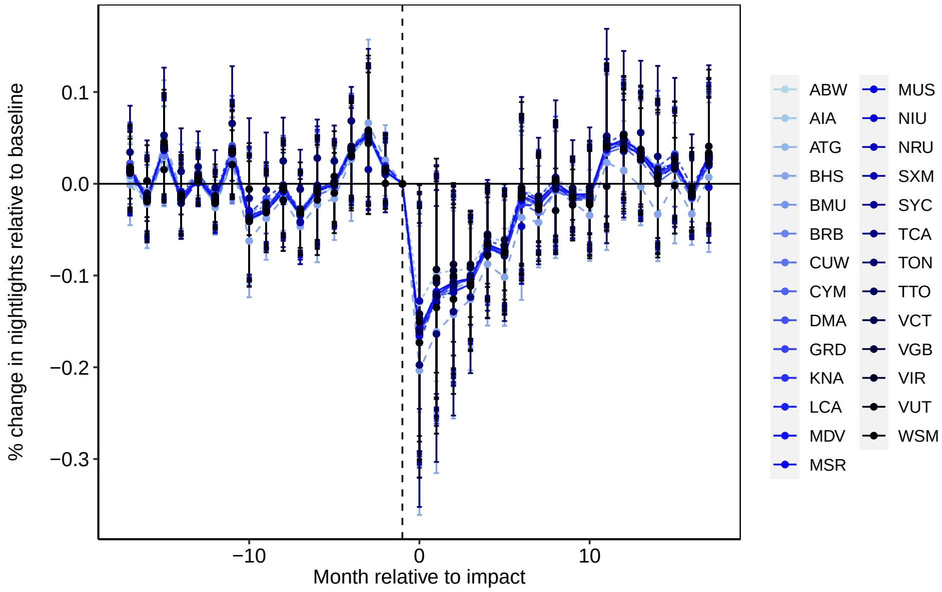
(b) Non-OFC sample: positive correlation



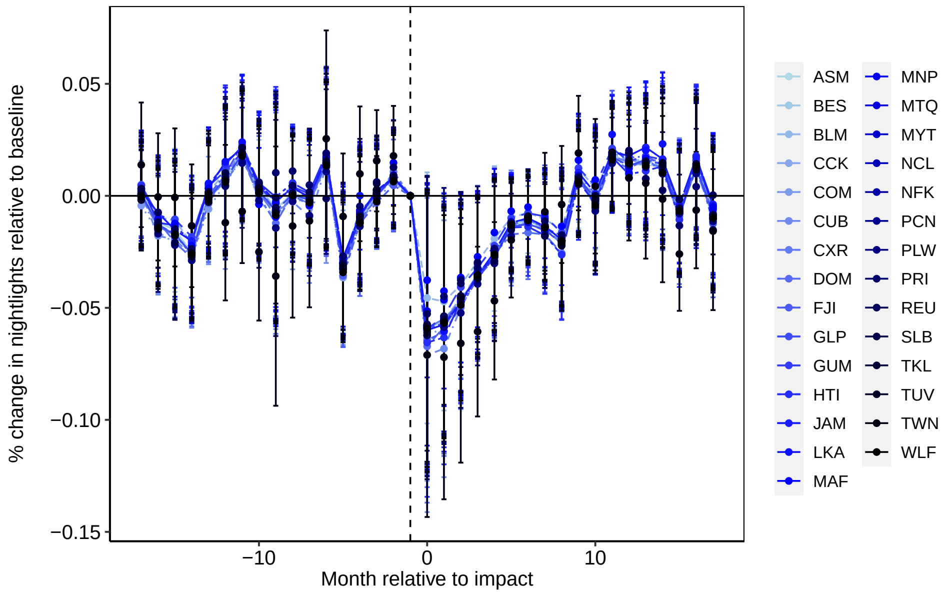
Notes: Both figures plot the inverse hyperbolic sine of nightlights aggregated by quarter over the inverse hyperbolic sine of mirror claims reported by non-OFC economies. The sample is limited by the availability of offshore mirror claims. Panel (a) shows the OFC part of the sample, panel (b) shows the non-offshore part of the sample.

Figure 9: Sample robustness of nightlight results: excluding each country in turn

(a) OFCs



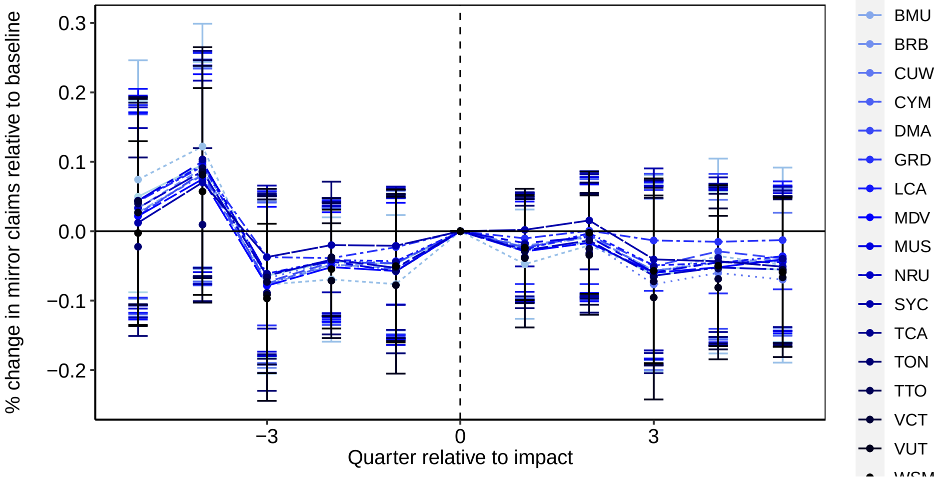
(b) non-OFCs



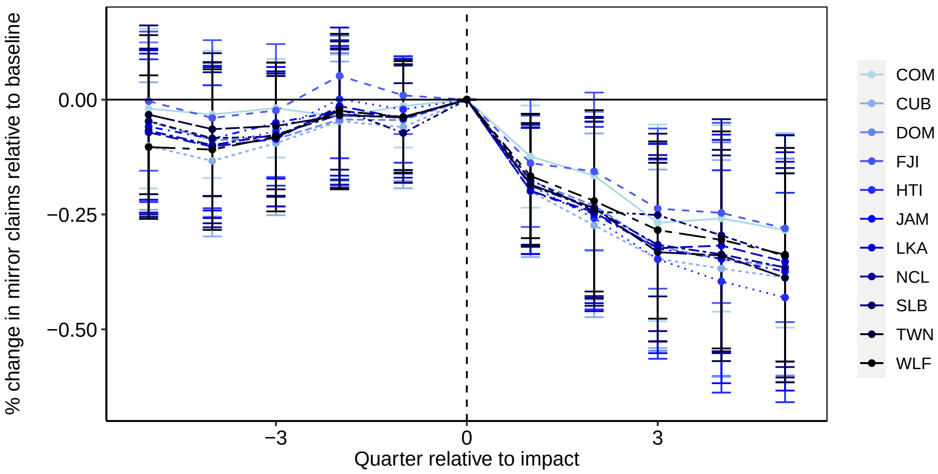
Notes: Plots coefficients of the multiple event study with binned endpoints outlined in the main text for monthly data. The estimation takes the following form: $i.h.s.(y_{it}) = \sum_{t=\underline{j}}^{\bar{j}} \beta_j b_{it}^j + \mu_i + \theta_t + \varepsilon_{it}$, notation being identical to the main text and b_{it}^j collecting event study dummies as well as binned endpoints. The baseline dummy left out of the regression is the month before the hurricane ($j = -1$) and 95% confidence intervals are plotted based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level. The top panel shows results for the OFC part of the sample, the bottom panel for the non-OFCs part of the sample. In both sub-samples, each country is excluded in turn and results for the rest of the sub-sample are plotted.

Figure 10: Sample robustness of mirror claim results: excluding each country in turn

(a) OFCs



(b) non-OFCs



Notes: Plots coefficients of the multiple event study with binned endpoints outlined in the main text for quarterly data. The estimation takes the following form: $i.h.s.(y_{it}) = \sum_{t=\underline{j}}^{\bar{j}} \beta_j b_{it}^j + \mu_i + \theta_t + \varepsilon_{it}$, notation being identical to the main text and b_{it}^j collecting event study dummies as well as binned endpoints. The baseline dummy left out of the regression is the quarter of the hurricane ($j = 0$) and 95% confidence intervals are plotted based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level. The top panel shows results for the OFC part of the sample, the bottom panel for the non-OFCs part of the sample.

Table 5: Robustness to different OFC categorizations: Mirrorclaims

	Dependent variable: i.h.s.(mirror claims)					
sample:		OFCs			non-OFCs	
tax-haven list:	Gr15	JZ14	HR94	Gr15	JZ14	HR94
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{hurricane}_{j=1:j=5}$	0.057	0.060	0.042	-0.317^{***}	-0.301^{***}	-0.234^{*}
	(0.093)	(0.093)	(0.077)	(0.094)	(0.078)	(0.121)
$\text{bin}_{j=\underline{j}:j=-6}$	0.035	-0.017	-0.008	-0.117	-0.071	-0.118^{*}
	(0.098)	(0.106)	(0.081)	(0.079)	(0.073)	(0.070)
$\text{bin}_{j=6:j=\bar{j}}$	-0.016	0.052	-0.173^{**}	-0.119	-0.179^{**}	-0.011
	(0.112)	(0.134)	(0.088)	(0.094)	(0.075)	(0.105)
country f.e.	Yes	Yes	Yes	Yes	Yes	Yes
year-qtr f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	519	462	346	346	403	519
R^2	0.171	0.217	0.231	0.173	0.193	0.129

Notes: Shows results of differences-in-differences specifications that change the assignment of islands into OFCs and non-OFCs based on lists in the literature. The first three columns show results for OFCs, the last three columns for non-OFCs. Columns 1 and 5 employ the list provided by Gravelle (2015). Columns 2 and 4 change this list to the one provided in Johannesen and Zucman (2014). Columns 3 and 6 finally use the older list of Hines and Rice (1994). The hurricane dummy collects coefficients of the first 6 quarters after a hurricane impact and both lower and upper bins are shown below. Effects therefore can be interpreted relative to the 6 quarters prior to a hurricane. *p<0.1; **p<0.05; ***p<0.01 based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

Annex

to accompany

"THE ELUSIVE BANKER: USING HURRICANES TO UNCOVER (NON-)ACTIVITY IN OFFSHORE FINANCIAL CENTERS"

Jakob Miethe

Includes:

Annex **A.1**: Details on sample choices and BIS balancing

Annex **A.2**: Further results on hurricane impacts

Annex **A.3**: Further extended results

Annex **A.4**: Further robustness tests

A.1. Data

A.1.1. Sample Choices

This Annex provides further information about the sample choices used here. Table A.1.1 shows all islands on the planet in the first column. If available, the second column shows the iso3 character code accepted by the United Nations, followed by the area in km^2. The next seven columns show reasons for exclusion from the sample indicating if the island is not in hurricane prone oceans (column 4), has no iso3 code recognized by the UN (column 5), is landlocked (column 6), uninhabited (column 7), larger than Cuba (column 8 with details of land area shown in figure A.1.1), or has a larger exclusive economic zone (EEZ) than the Solomon Islands (column 9 with details of EEZ distribution of all islands shown in figure A.1.2). The two figures (A.1.1 and A.1.2) are shown below and indicate with dashed lines where the sample was cut. The largest country still included is indicated in green in those figures. These sample choices provide a relatively large sample of comparable islands in hurricane areas.

Table A.1.1: Sample Exclusion Choices

country	iso3c	area in km^2	other oceans	no iso3	landlocked	uninhabited	area > Cuba	eez > Solomon Isl.	in sample
American Samoa	ASM	199							1
Anguilla	AIA	91							1
Antigua & Barbuda	ATG	440							1
Aruba	ABW	180							1
Bahamas	BHS	13,878							1
Barbados	BRB	431							1
Bermuda	BMU	53							1
British Virgin Islands	VGB	151							1
Caribbean Netherlands	BES	328							1
Cayman Islands	CYM	259							1
Christmas Island	CXR	135							1
Cocos (Keeling) Islands	CCK	14							1
Comoros	COM	1,659							1
Cuba	CUB	109,884							1
Curaçao	CUW	444							1

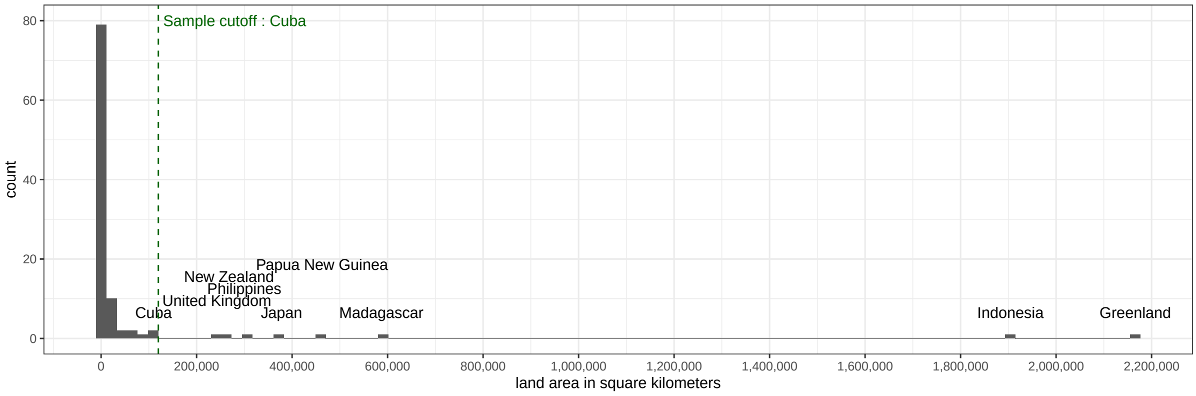
Dominica	DMA	750							1
Dominican Republic	DOM	48,442							1
Fiji	FJI	18,333							1
Grenada	GRD	348							1
Guadeloupe	GLP	1,628							1
Guam	GUM	549							1
Haiti	HTI	27,750							1
Jamaica	JAM	10,992							1
Maldives	MDV	298							1
Martinique	MTQ	1,128							1
Mauritius	MUS	1,040							1
Mayotte	MYT	374							1
Montserrat	MSR	201							1
Nauru	NRU	21							1
New Caledonia	NCL	18,575							1
Niue	NIU	261							1
Norfolk Island	NFK	35							1
Northern Mariana Islands	MNP	477							1
Palau	PLW	458							1
Pitcairn Islands	PCN	47							1
Puerto Rico	PRI	13,800							1
Réunion	REU	2,512							1
Saint Martin (French part)	MAF	53							1
Samoa	WSM	2,842							1
Seychelles	SYC	459							1
Sint Maarten	SXM	34							1
Solomon Islands	SLB	28,399							1
Sri Lanka	LKA	65,610							1
St. Barthélemy	BLM	24							1
St. Kitts & Nevis	KNA	261							1
St. Lucia	LCA	617							1
St. Vincent & Grenadines	VCT	389							1
Taiwan	TWN	36,193							1
Tokelau	TKL	10							1
Tonga	TON	747							1
Trinidad & Tobago	TTO	5,131							1
Turks & Caicos Islands	TCA	417							1
Tuvalu	TUV	26							1
U.S. Virgin Islands	VIR	346							1
Vanuatu	VUT	12,199							1
Wallis & Futuna	WLF	142							1
Akrotiri and Dhekelia		254	1	1					
Aland	ALA	1,580	1						
Azores		2,351	1	1					
Bahrain	BHR	750			1				
Baker Island		2		1					
British Indian Ocean Territory	IOT	60				1			
Brunei	BRN	5,765			1				
Canary Islands		7,492	1	1					
Cape Verde	CPV	4,033	1						
Clipperton Island	XCL	9				1			

Cook Islands	COK	236						1
Cyprus	CYP	9,251	1					
Easter Island		164		1				
Falkland Islands	FLK	12,173	1					
Faroe Islands	FRO	1,399	1					
French Polynesia	PYF	4,167						1
French Southern Territories	ATF	7,676				1		1
Greenland	GRL	2,166,086	1				1	1
Guernsey	GGY	78	1					
Heard & McDonald Islands	HMD	368				1		
Hong Kong SAR China	HKG	1,106			1			
Iceland	ISL	103,000	1					
Indonesia	IDN	1,904,569					1	1
Ireland	IRL	84,421	1					
Isle of Man	IMN	572	1					
Japan	JPN	377,915					1	1
Jersey	JEY	119	1					
Kiribati	KIR	811						1
Macao SAR China	MAC	115			1			
Madagascar	MDG	587,041					1	
Malta	MLT	316	1					
Marshall Islands	MHL	181						1
Micronesia	FSM	702						1
Navassa Island		5		1		1		
New Zealand	NZL	268,021					1	1
Papua New Guinea	PNG	462,840			1		1	1
Paracel Islands		8		1		1		
Philippines	PHL	300,000					1	1
Singapore	SGP	721			1			
South Georgia & South Sandwich Islands	SGS	3,903	1			1		
Spratly Islands		2		1		1		
St. Helena	SHN	122	1					
St. Pierre & Miquelon	SPM	242	1					
Svalbard & Jan Mayen	SJM	61,359	1					
São Tomé & Príncipe	STP	1,001	1					
Timor-Leste	TLS	15,006			1			
United Kingdom	GBR	242,495	1				1	
United States Minor Outlying Islands (the)	UMI	34				1		

A.1.2. BIS balancing choices

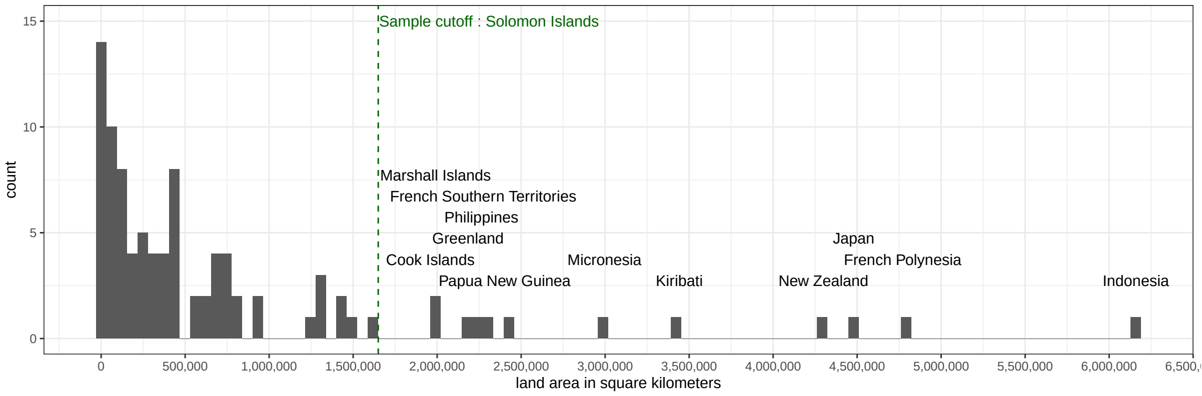
The Locational Banking Statistics (LBS) used in the main text are derived from reports of a reporting country against a large number of counterparties. The coverage of this dataset changes along both dimensions. A continuous increase is visible over time as shown in Figure A.1.3.

Figure A.1.1: Distribution of Island area and cutoff point



Notes: On the vertical axis, the histogram counts the number of islands of the area shown on the horizontal axis. Islands larger than Cuba are named in the graph. The vertical green dashed line shows the cutoff point at Cuba (109,238 square kilometers) which is the largest island in the sample. The next biggest island is the United Kingdom with 244,820 square kilometers.

Figure A.1.2: Distribution of Exclusive Economic Zones and cutoff point

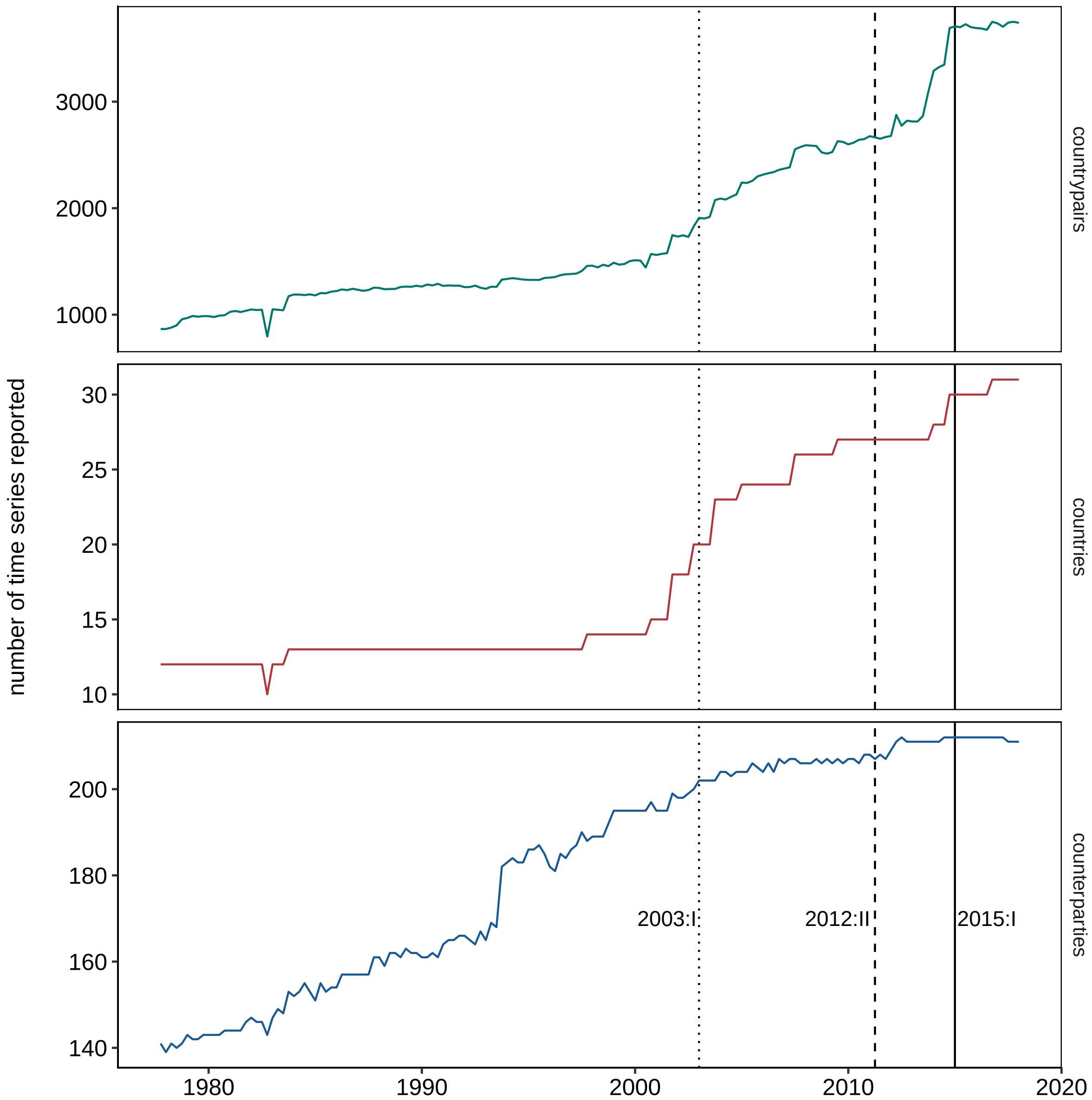


Notes: On the vertical axis, the histogram counts the number of islands of the EEZ size shown on the horizontal axis. Islands with an EEZ larger than that of the Solomon Islands are named in the graph. The vertical green dashed line shows the cutoff point at the Solomon Islands (1,589,477 square kilometers) which is the largest EEZ island in the sample. The next biggest EEZ is that of the Cook Islands with 1,960,027 square kilometers.

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 shown in Figure A.1.4, this increase 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.1.3 shows the panel available for balancing in 2015:I) report relatively small positions that follow similar trends.

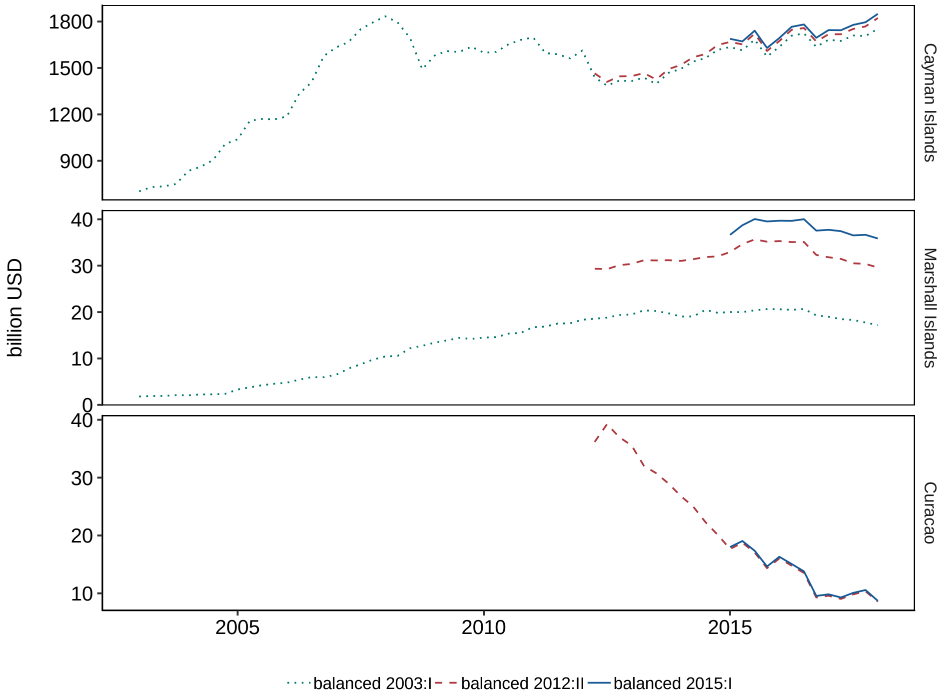
Figure A.1.4 in the plots national mirror claims against three exemplary islands to highlight effect of different balancing choices. The green dotted line shows a sample balanced in 2003:I to checked if reporting increased substantially before 2012:II. The red dashed line shows a sample balanced in 2012:II where nightlight becomes available. These are the series used in this study. The solid blue line shows a sample balanced in 2015:I. These series allow some initial observations. 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 do not deviate much and that both the level and the dynamics are well captured by the series balanced in the second quarter of 2012. The Marshall Islands have received much less scrutiny and coverage is still increasing as more and more countries start reporting data against them. This is evident in the level shift between the three series. Still, the time dynamics especially of the 2015:I series seem well captured in the 2012:II series used. Some OFCs, such as Curacao (bottom panel) exhibit decreasing deposits over time. Since Curacao split from Sint Maarten and Bonaire (formerly the Netherlands Antilles) in 2010, the 2003:I series cannot be compared here, but the 2012:II and the 2015:I series are closely aligned. They do show, however, how fickle international financial positions can be for OFCs with mirrorclaims dropping from around 40 billion USD in 2012 to only two billion USD in 2017. Figure A.1.4 also shows that OFCs vary substantially in their ability to attract international bank funding over time.

Figure A.1.3: 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 that are plotted in Figure A.1.4 below: 2003:I, 2012:II and 2015:I. The series balanced in 2012:II are used in the main text.

Figure A.1.4: Balanced mirror claims of three exemplary 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 2012:II (red, dashed, used in the main text), 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.

A.2. Further results on hurricane impacts

This Annex shows further results for nightlight impacts. First, results on the impact of hurricanes Irma and Maria in September 2017 in the Caribbean are presented as a case study before results on regional data are presented. Figures A.2.1 and A.2.2 plot a part of the Caribbean 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, are only added for the British Virgin Islands. The nightlight intensity inside that area would then be used to calculate monthly statistics. The top panel shows the map in August 2017, the bottom panel in October 2017. Hurricanes Irma and Maria hit the British Virgin Islands in September 2017 and the drop in nightlight intensity after these hurricanes is visible between the two maps.

Using the monthly nightlight dataset outlined in the data section, Figure A.2.3 compares 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 is standardized for each island and then averaged for islands affected by the storms (green line) and non-affected islands (red line). Pre-trends show that both groups of islands fluctuate together very closely until the hurricane hits. After impact, the 90% (dark shading) and 95% confidence bands show a significant drop in nightlight intensity on affected islands.

Turning to regional data Figure A.2.4 plots the mean of nightlight intensity for all regions of the British Virgin Islands. Hurricanes Irma and Maria are clearly visible here for all regions but impacts are especially strong for the capital Tortola. Moving to the entire sample, Figure A.2.5 repeats the main analysis of hurricane impacts on nightlight intensity for capital regions only. If no sub-national administrative entities exist, national data was used again. These results confirm the effects visible in the main analysis and show an immediate and sustained effect of hurricanes on local conditions.

Figure A.2.1: Nightlights in the British Virgin Islands pre Irma & Maria

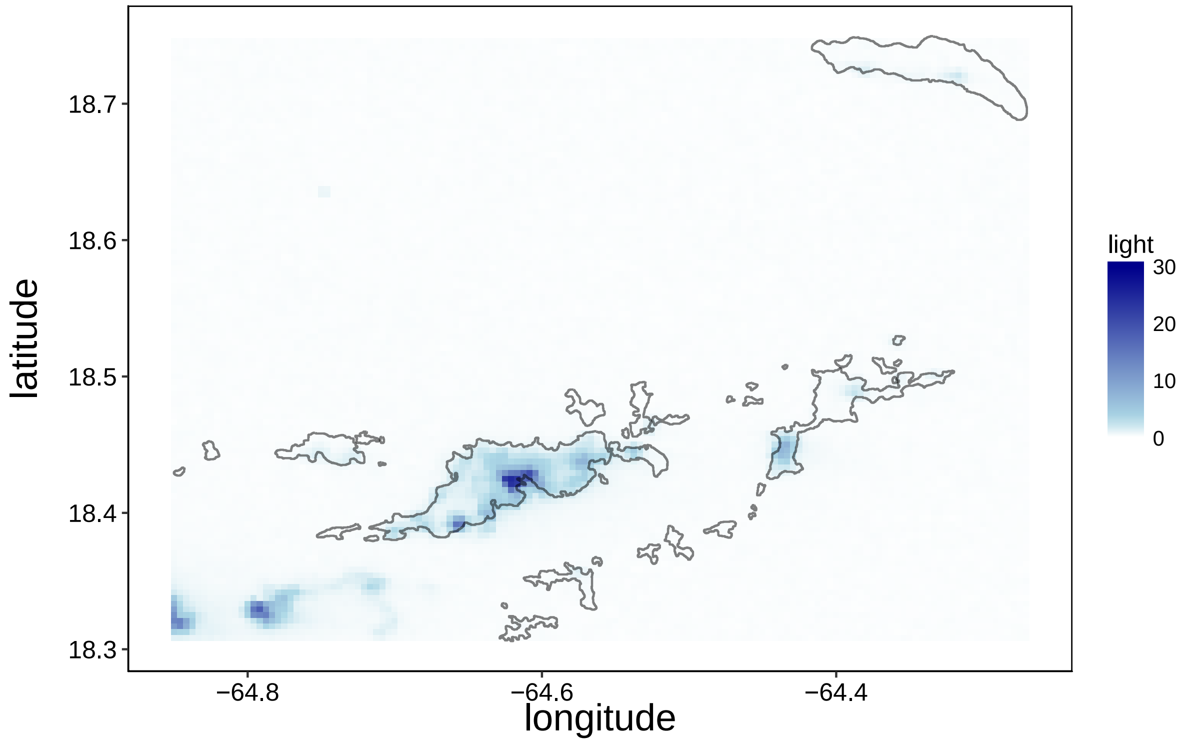
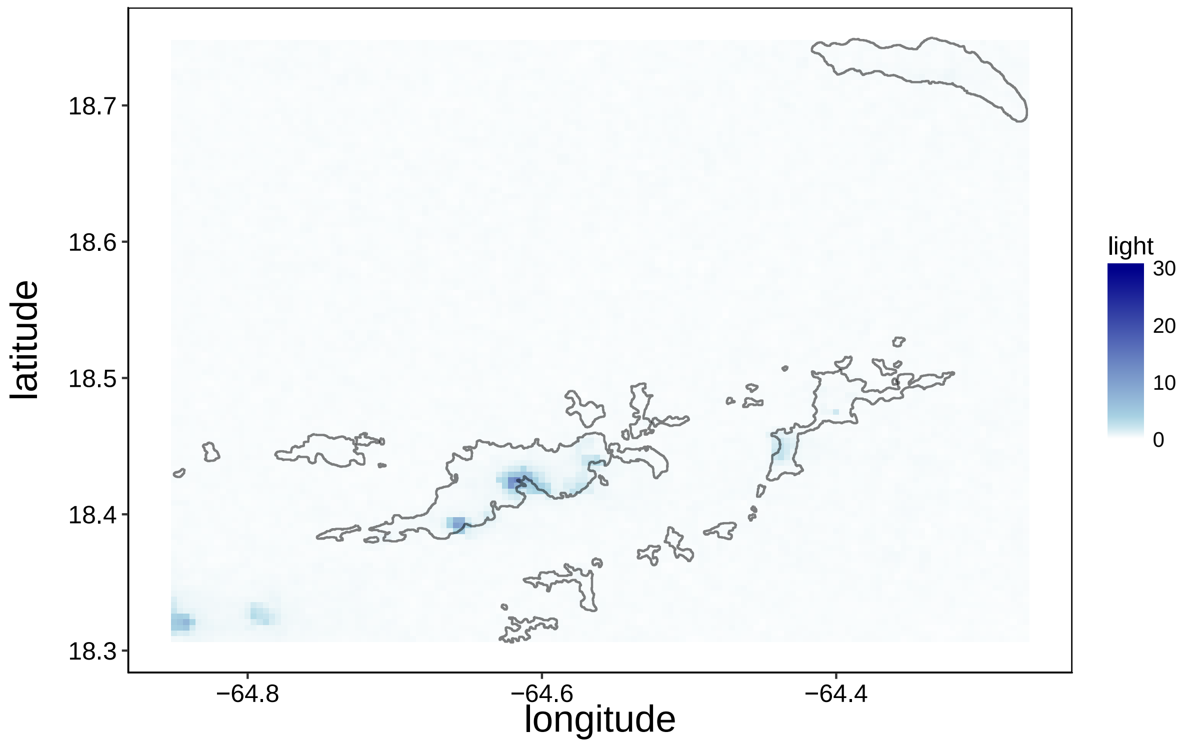
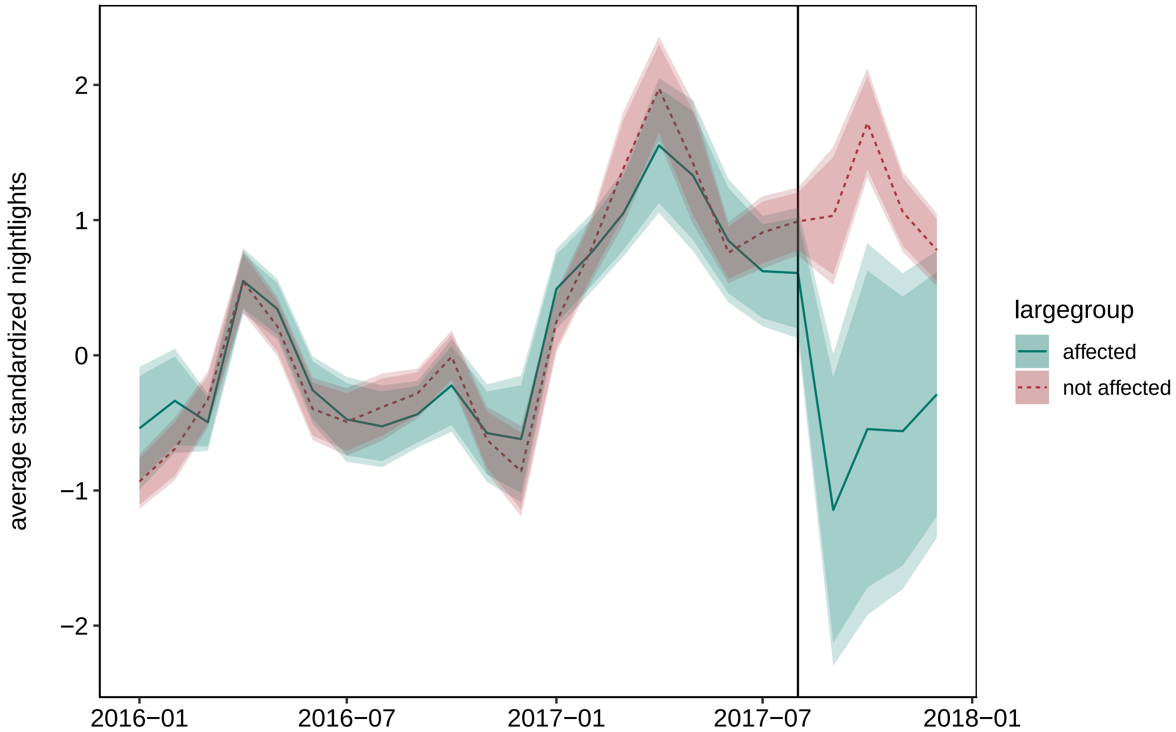


Figure A.2.2: **Nightlights in the British Virgin Islands post Irma & Maria**



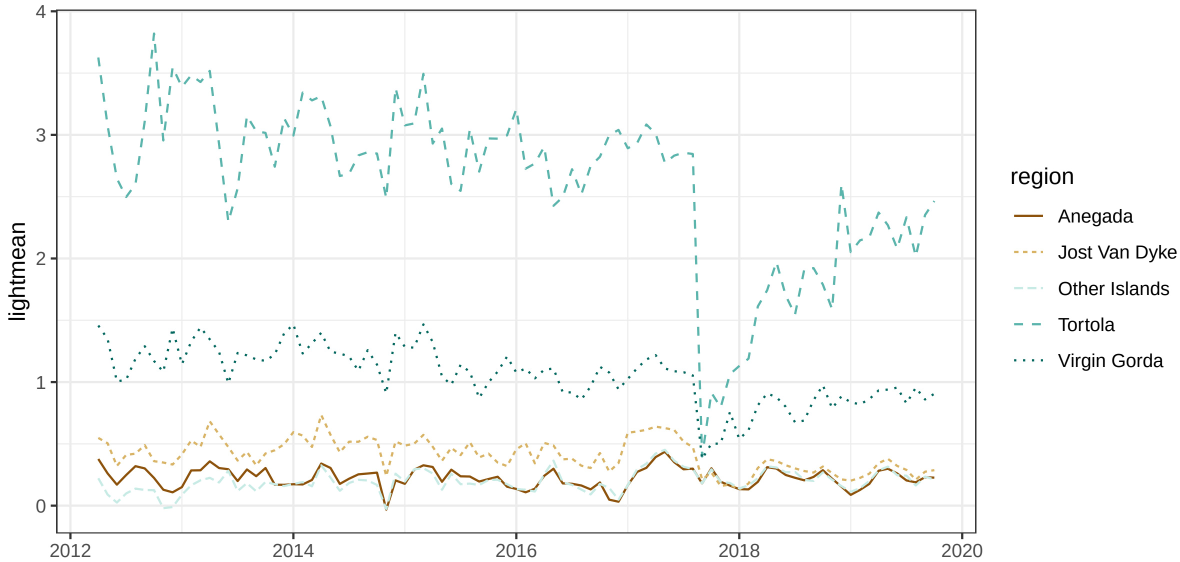
Notes: Shows nightlight intensity for the British Virgin Islands (center) and the US Virgin islands (south-west) and the country polygon (in grey borders) for the British Virgin Islands only. The top panel shows nightlight intensity in August 2017, before hurricanes Irma and Maria hit the islands. The bottom panel 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 local conditions. Radiance of nightlight is measured in units of $Wcm^{-2}sr^{-1}$, or watt per steradian per square centimeter multiplied by $1E9$.

Figure A.2.3: Impacts of hurricanes Irma & Maria on nightlight intensity



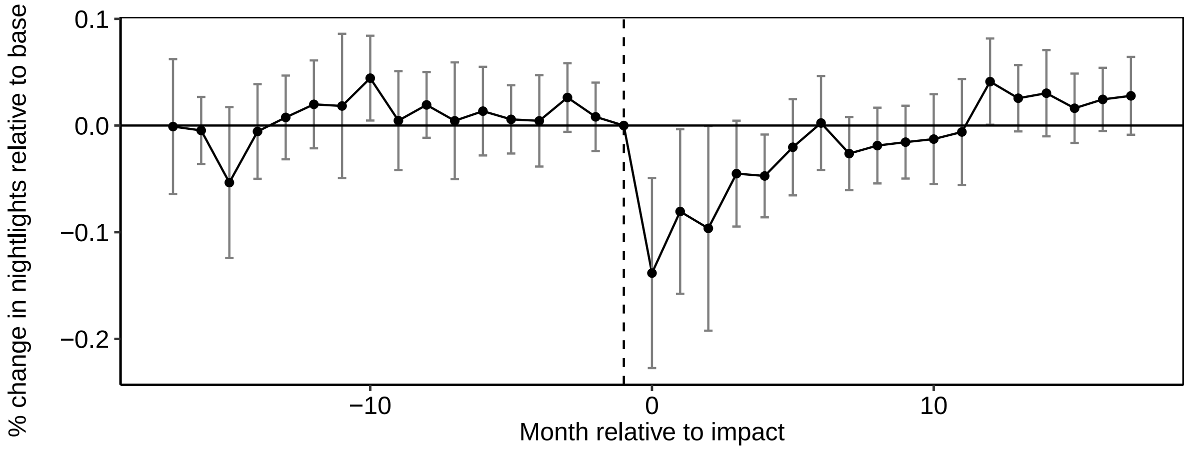
Notes: The figure plots average nightlight intensity in the sample starting in 2016 till January 2018. The vertical line indicates September 2017 when hurricanes Irma and Maria hit the Caribbean. Countries are categorized into affected (green) and non-affected (red). All series are standardized at the country level to eliminate level effects before being averaged within the two groups.

Figure A.2.4: Regional time series for nightlights in the British Virgin Islands



Notes: Shows time series for the regional nightlight data of the British Virgin Islands. Tortola is the capital region and the drop at the end of 2017 happens at the time of hurricanes Irma and Maria.

Figure A.2.5: Hurricane impacts on nightlights in capital regions



Notes: Plots coefficients of the multiple event study with binned endpoints outlined in the main text for monthly data constructed for capital regions only. When no sub-national classification was available in country polygons, the entire island was used again. The estimation takes the following form: $i.h.s.(y_{it}) = \sum_{t=\underline{j}}^{\bar{j}} \beta_j b_{it}^j + \mu_i + \theta_t + \varepsilon_{it}$, notation being identical to the main text and b_{it}^j collecting event study dummies as well as binned endpoints. The baseline dummy left out of the regression is the month before the hurricane ($j = -1$) and 95% confidence intervals are plotted in grey based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

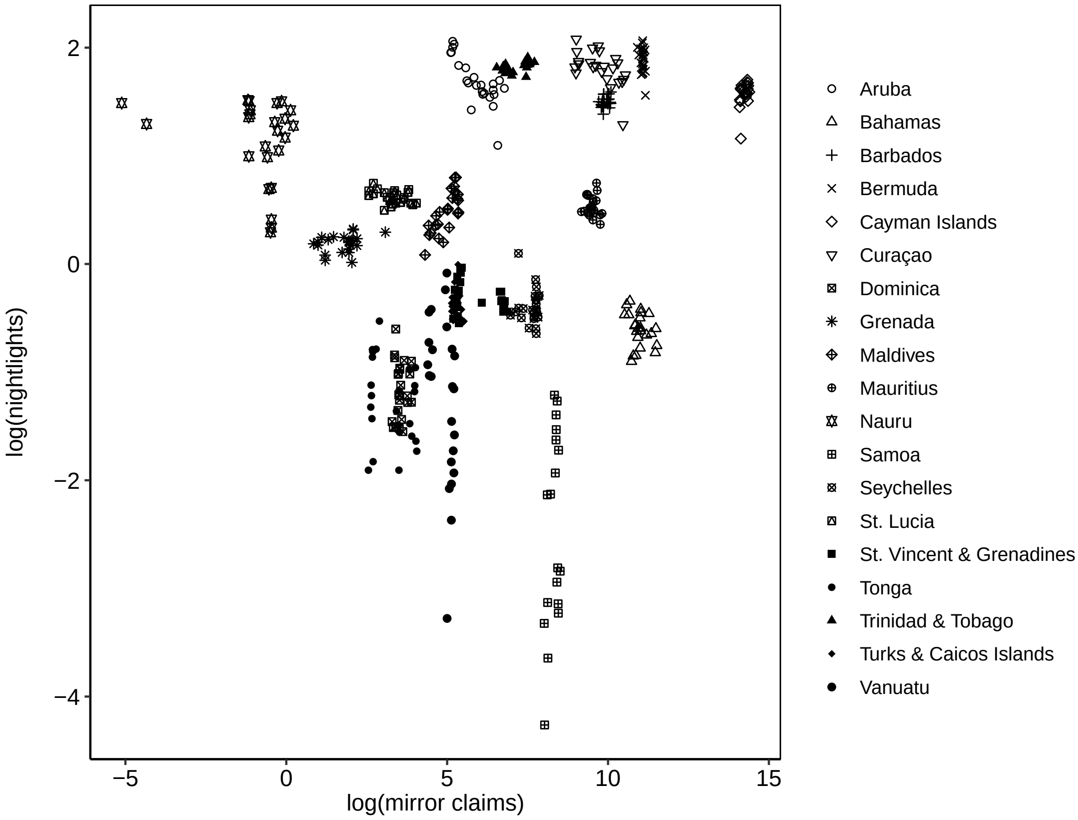
A.3. Further extended results

Figure A.3.1: Absolute changes in incorporation activity

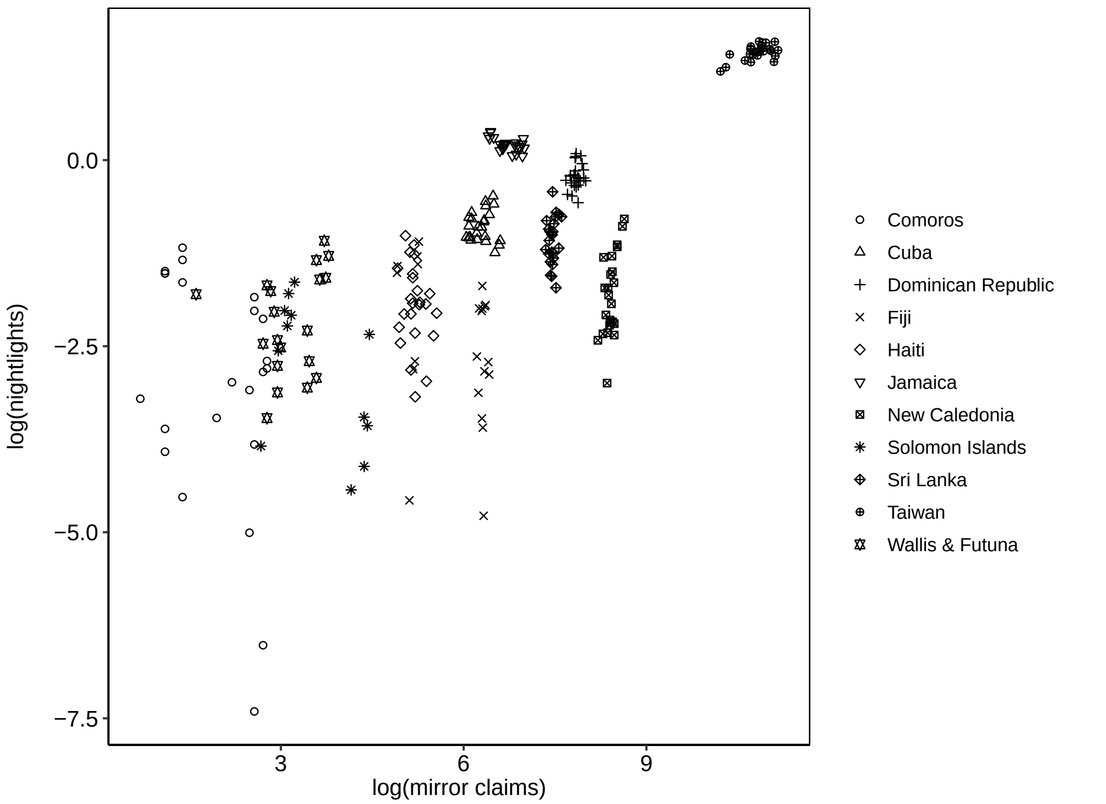
Notes: Shows the mean drop of incorporations on weekends, local holidays and holidays in Tokyo, New York, and London. All changes are compared to average incorporations on non-weekend workdays.

Figure A.3.2: Direct correlations of nightlights and mirror claims: Logs

(a) OFC sample



(b) Non-OFC sample



Notes: Both panels plot the log of nightlights over the log 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 OFC part of the sample where no correlation is visible. Panel (a) shows the non-offshore part of the sample with a positive relationship of both variables.

A.4. Further robustness tests

Table A.4.1: Robustness to different OFC categorizations: Mirrorclaims, no binned endpoints

	Dependent variable: log(mirror claims)					
sample:		OFCs			non-OFCs	
tax-haven list:	Gr15	JZ14	HR94	Gr15	JZ14	HR94
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{hurricane}_{j=1:j=5}$	0.052	0.049	0.090	-0.214^{**}	-0.200^{***}	-0.168^{*}
	(0.110)	(0.117)	(0.083)	(0.085)	(0.064)	(0.098)
country f.e.	Yes	Yes	Yes	Yes	Yes	Yes
year-qtr f.e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	519	462	346	346	403	519
R^2	0.169	0.214	0.186	0.137	0.132	0.104

Notes: Shows results of differences-in-differences specifications that change the assignment of islands into OFCs and non-OFCs based on lists in the literature without using binned endpoints. The first three columns show results for OFCs, the last three columns for non-OFCs. Columns 1 and 5 employ the list provided by Gravelle (2015). Columns 2 and 4 change this list to the one provided in Johannesen and Zucman (2014). Columns 3 and 6 finally use the older list of Hines and Rice (1994). The hurricane dummy collects coefficients of the first 6 quarters after a hurricane impact. Without binned endpoints, effects can be interpreted relative to all non-hurricane periods. *p<0.1; **p<0.05; ***p<0.01 based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

Table A.4.2: Quantifying nightlight impacts: no binned endpoints

	Dependent variable:			
	log(nightlight intensity)		i.h.s.(nightlight intensity)	
	OFCs	non-OFCs	OFCs	non-OFCs
	(1)	(2)	(3)	(4)
$\text{hurricane}_{j=0:j=8}$	-0.217^{***}	-0.250^{***}	-0.111^{**}	-0.070^{**}
	(0.064)	(0.059)	(0.044)	(0.027)
country f.e.	Yes	Yes	Yes	Yes
year-qtr f.e.	Yes	Yes	Yes	Yes
Observations	2,145	2,189	2,187	2,349
R^2	0.163	0.277	0.174	0.275

Notes: Shows results of a difference in difference exercise with a dummy ($\text{hurricane}_{j=0:j=9}$) taking value 1 if there was a hurricane in the last nine year-months. All results are reported split-sample first showing the OFC part of the sample, then the non-OFC part of the sample. Columns 1 and 2 show results using the log of nightlight intensity, colums 3 and 4 using the inverse hyperbolic sine transformations. Without binned endpoints, effects can be interpreted relative to all non-hurricane periods. *p<0.1; **p<0.05; ***p<0.01 based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

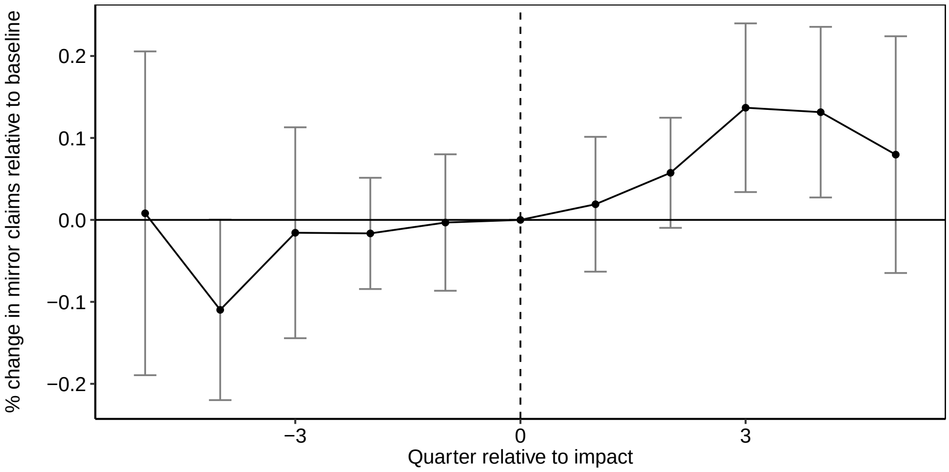
Table A.4.3: Further results using BIS data: no binned endpoints

dependent var.:	mirror claims			mirror liabilities	
sample:	OFCs (1)	non-OFCs (2)	all (3)	OFCs (4)	non-OFCs (5)
$\text{hurricane}_{j=1:j=6}$	0.008	-0.228^{***}		0.064	0.053
	(0.083)	(0.082)		(0.075)	(0.047)
$\text{hurricane}_{j=1:j=6}\times$ OFCs			-0.044		
			(0.072)		
$\text{hurricane}_{j=1:j=6}\times$ non-OFCs			-0.152^{**}		
			(0.076)		
country f.e.	Yes	Yes	Yes	Yes	Yes
year-qtr f.e.	Yes	Yes	Yes	Yes	Yes
Observations	548	317	865	548	344
R^2	0.220	0.158	0.123	0.038	0.083

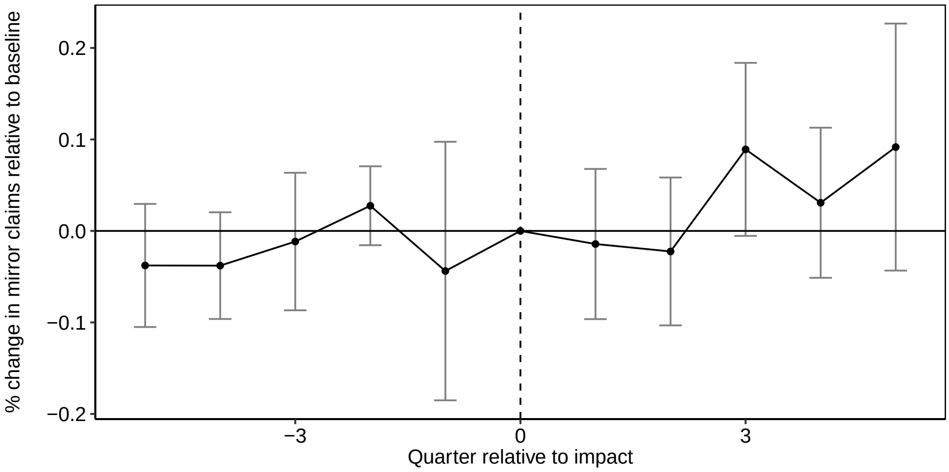
Notes: Shows results of a difference in difference exercise with a dummy ($\text{hurricane}_{j=1:j=6}$) taking value 1 if there was a hurricane in the last six year-quarters. All results are reported split-sample first showing the OFC part of the sample, then the non-OFC part of the sample. Columns 1 to 3 show results on all mirror claims for OFCs (1) non-OFCs (2) and the entire sample using an interaction term on OFCs and non-OFCs (3). Columns 4 and 5 report a falsification exercise showing results on all liabilities reported against islands in the sample. Without binned endpoints, effects can be interpreted relative to all non-hurricane periods. *p<0.1; **p<0.05; ***p<0.01 based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

Figure A.4.1: Falsification using liabilities: Event Study

(a) OFC sample

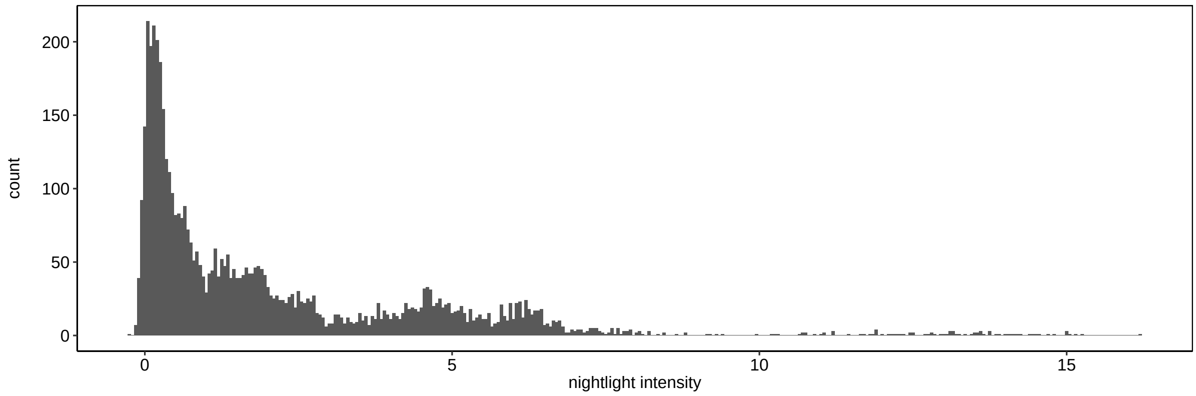


(b) non-OFC sample



Notes: Plots coefficients of the multiple event study with binned endpoints outlined in the main text for quarterly data on passive deposits in non-OFC BIS reporting countries. The estimation takes the following form: $i.h.s.(y_{it}) = \sum_{t=\underline{j}}^{\bar{j}} \beta_j b_{it}^j + \mu_i + \theta_t + \varepsilon_{it}$, notation being identical to the main text and b_{it}^j collecting event study dummies as well as binned endpoints. The baseline dummy left out of the regression is the quarter of the hurricane ($j = 0$) and 95% confidence intervals are plotted in error bars based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level. The top panel shows results for the OFC part of the sample, the bottom panel for the non-OFCs part of the sample.

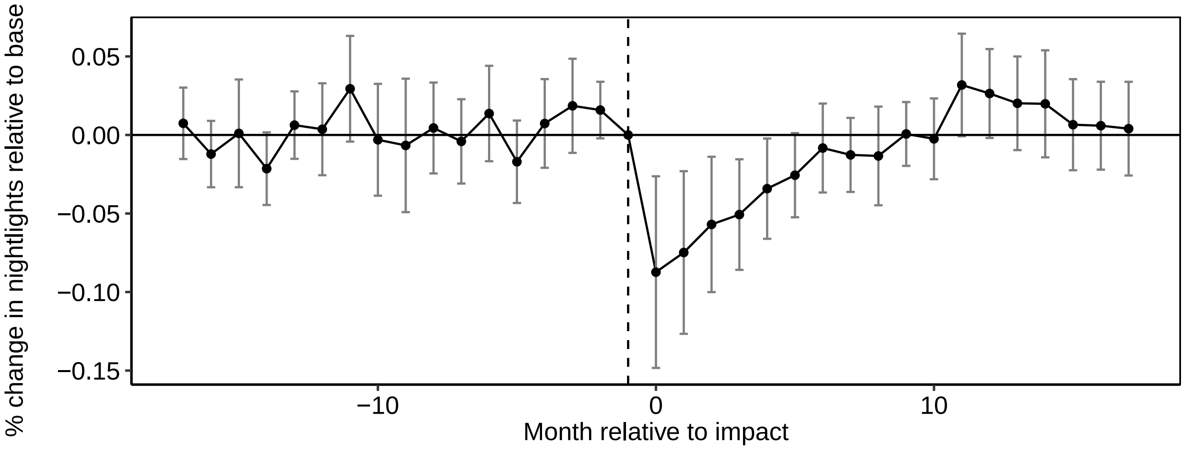
Figure A.4.3: Distribution of nightlight intensity



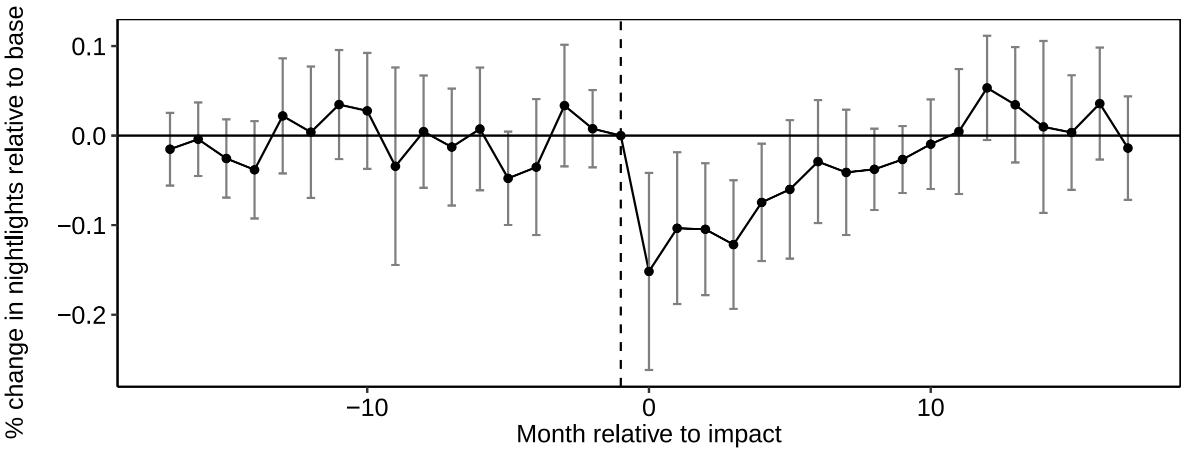
Notes: On the vertical axis, the histogram counts the number of observations that exhibit the nightlight intensity plotted on the horizontal axis.

Figure A.4.4: Event studies using i.h.s., log, and level specifications

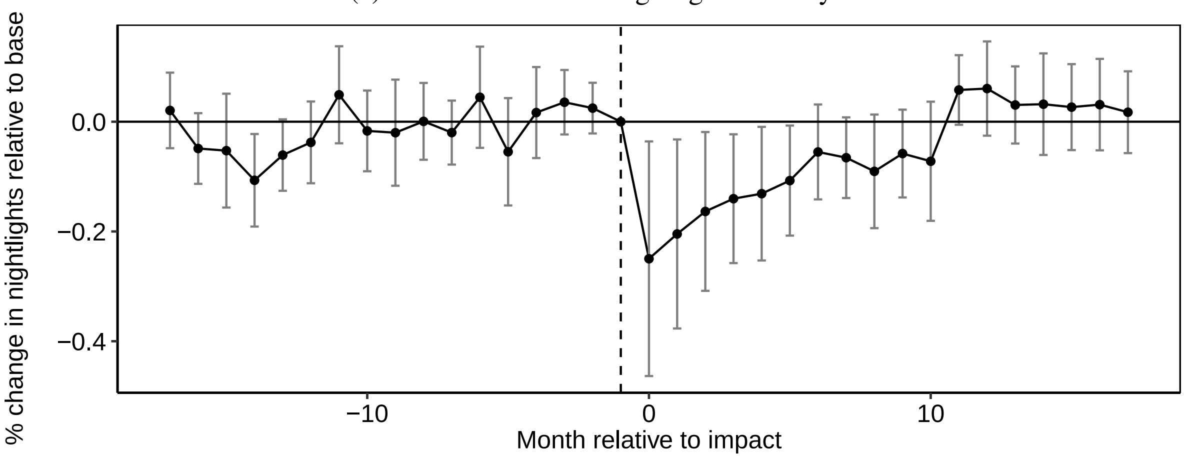
(a) Outcome variable: i.h.s(nightlight intensity)



(b) Outcome variable: log(nightlight intensity), sample reduced to positives



(c) Outcome variable: nightlight intensity



Notes: Shows the event study of the main text for hurricane impacts on nightlight intensity for the entire sample. The baseline dummy left out of the regression is the month before the hurricane ($j = -1$) and 95% confidence intervals are plotted in grey, based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level. The top panel uses the inverse hyperbolic sine transformation that is used in the main text. The middle panel reduces the sample to countries without negative and 0 values for nightlight intensity and shows results of log-transformed data. The bottom panel finally uses the nightlight data in levels.