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Do Capital Inflows Spur Technology Diffusion?

Evidence from a New Technology Adoption Index

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Do Capital Inflows Spur Technology Diffusion? Evidence from a New Technology Adoption Index
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ABSTRACT: We construct a novel measure of technology adoption, the Embodied Technology Imports Indicator (ETI), available for 181 countries over the period 1970-2020. The ETI measures the technological intensity of imports of each country by leveraging patent data from PATSTAT and product-level trade data from COMTRADE. We use this index to assess the link between capital flows and the diffusion of new technologies across emerging economies and low-income countries. Through a local projection difference-in-differences approach, we establish that variations in statutory capital flow regulations increase technological intensity by 7-9 percentage points over 5 to 10 years. This increase is accompanied by a significant 28-33 pp rise in the volume of gross capital inflows, driven primarily by foreign direct investment (21 pp increase), and a 9 to 12 percentage points shift in the level of Real GDP per capita in PPP terms.

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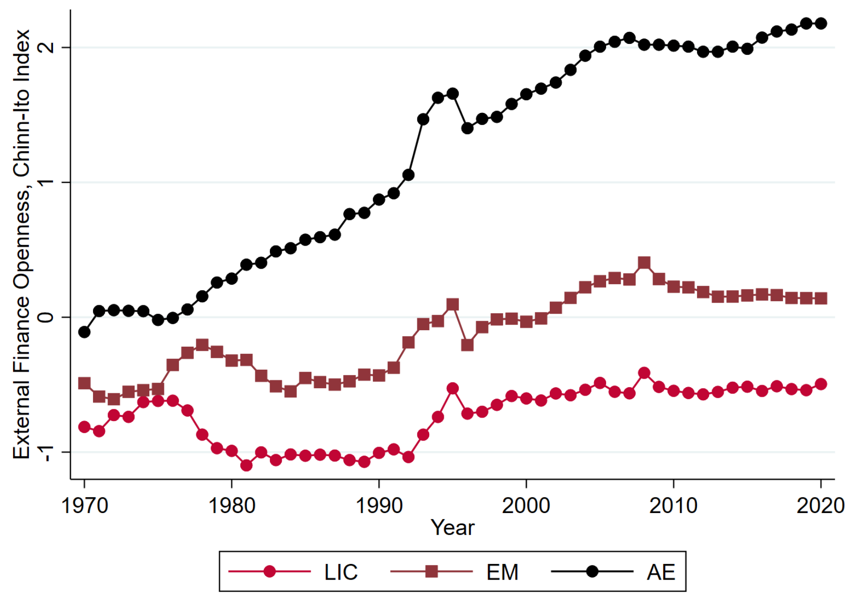
1 Introduction

Should countries liberalize their capital account and allow free movement of capitals? While a burgeoning literature has highlighted the desirability of temporary capital flow management measures ("gates") to moderate boom and bust cycles (Erten et al. 2021), the removal of longstanding, non-state-dependent restrictions ("walls") is generally considered beneficial (Kose et al. 2009, IMF 2012). In spite of this consensus, the empirical evidence quantifying the effects and transmission channels of liberalization has been more elusive. In this paper, we focus on a specific channel often associated with capital flows but for which evidence remains scant: technology diffusion to emerging markets and developing economies (EMDEs). This aspect is highly relevant since countries with lower income levels and technological capabilities are still considerably less open to international financial flows than advanced economies (see Figure 1). Furthermore, rising tensions from geoeconomic fragmentation threaten to impose additional hurdles to international trade and financial flows, which would negatively impact convergence under the consensus view that capital flows aid knowledge diffusion (IMF 2023). While some studies have linked FDIs and invention activity (e.g., Chen et al. (2022)), their use of patent data prevented any analysis of lower-income countries, where patenting activity is limited and technologies are often adopted from abroad rather than developed domestically (Eaton & Kortum 2001). In fact, there is a general lack of cross-country data on technology adoption in EMDEs, with only few notable exceptions (Comin & Mestieri 2014).

Motivated by the fact that EMDEs often adopt foreign technology, rather than developing it domestically, we propose a new indicator of technology adoption, the Embodied Technology Imports Indicator (ETI), which tracks the average technological content of each country's imports of capital goods. For each importer, we build the ETI as the average of trade partners' technology score weighted by their share in the country's imports of capital goods. We construct technology scores using patent data from the PATSTAT dataset, which contains information on 90 patent-issuing authorities from the year 1900 to the present day. Each country's score is determined by the stock of granted patent families registered in the relevant patent office, which we attribute to the commodities in the UN COMTRADE data set using a crosswalk between International Patent Classification (IPC) and SITC Rev. 1 codes. The resulting data covers 181 countries (155 EMDEs) for the period 1970-2020. We validate our indicator and its inputs against alternative data sources. First, we verify that partner country's technology scores in capital goods are positively correlated with their world share of capital exports, with exports of intellectual property services as measured by the WTO-OECD Balanced Trade in Services (BATIS) data set, as well as the Economic Complexity Index (ECI) built by Hausmann et al. (2014). Second, and more relevant to our

Figure 1: Capital Openness over Time, by Income Group



Note: This figure displays the time series for capital openness as measured by the Chinn & Ito (2008) index over the period 1970-2020. The three series represent the simple average of the measure for countries belonging to different income groups as defined by the IMF's World Economic Outlook: low-income developing countries (LIDC), emerging markets (EM), and advanced economies (AE).

analysis, we show that the ETI has a strong positive correlation with *imports* of intellectual property, suggesting that our indicator is indeed associated with knowledge flows, and that increases in the ETI predict future GDP PPP per capita growth.

Our empirical analysis follows and event-study design around plausibly exogenous episodes of *de jure* financial liberalization over the period 1970-2020, as captured by increases in the KAOPEN index developed by Chinn & Ito (2008). We employ the novel local projection difference-in-differences approach of Dube et al. (2023), which allows a precise identification of treatment and control groups in settings where units are treated repeatedly at different dates, as is the case in our sample. We focus on three sets of outcomes for the 90 episodes that we identify. First, we assess the effectiveness of financial liberalization, showing that gross capital inflows increase by $28-33\%$ over 5 to 10 years following our episodes, driven primarily by FDI flows. Second, coming to our main outcome of interest, we show that the ETI increases by $7-9\%$ over the same horizon, providing evidence that financial liberalization spurs adoption of newer technologies. Finally, we estimate that financial liberalization causes an increase in the level of Real GDP per capita in PPP terms of $9-12$ percentage points over 5 to 10 years. Our results provide suggestive evidence that capital flows allow for investment in more modern technology, which in turn increases output.

Related Literature. This paper is related to two strands of the literature. First, it contributes to the literature on measuring technology adoption and diffusion. A long tradition in this strand has used patent citations to measure technology spillovers across space and countries (see, e.g., Jaffe et al. (1993), Peri (2005), Griffith et al. (2011), Bloom et al. (2013), Fons-Rosen et al. (2021), Cai et al. (2022) and additional references therein). The focus on patents—and therefore *invention* activities—constrained the scope of these insightful studies to advanced economies or frontier emerging markets, where patenting activity is concentrated. Motivated by the fact that lower-income countries often innovate through *adoption* of inventions developed elsewhere (Eaton & Kortum 2001, Comin & Mestieri 2014, Zanello et al. 2016, Mutreja et al. 2018), other studies have focused on the diffusion of specific technologies across countries (notably, Comin & Hobijn (2009), Comin & Hobijn (2010), Comin & Mestieri (2014) and Comin & Mestieri (2018)). In this paper, we present a novel measure that bridges these two strands building on the literature's findings that invention is concentrated in more advanced economies and diffuses to developing countries primarily through trade in goods that embody new technologies. This approach allows us to move beyond a narrowly-defined list of specific technologies, since our indicator can be built for any chosen set of imported goods, and to cover a large number of countries and periods. Our indicator focuses on the technological sophistication of *production inputs*, and it is therefore markedly different from Hausmann et al.'s (2014) "Economic Complexity Index," which aims to capture the technological specialization of exports.[1]

Second, we contribute to the strand of the literature quantifying the effects of international capital flows, particularly on long-term outcomes like growth and productivity. As noted in Erten et al. (2021), studies in this strand tend to suffer from issues of endogeneity and poor measurement of capital flows. Kose et al. (2009) argue that these issues are the main culprit for the pervasive weakly identified or null results on the effect of external financial liberalization on GDP growth, a finding echoed by recent studies like Furceri et al. (2019).[2] Aside from methodological issues, Henry (2007) ascribes this dearth of evidence to an emphasis on long-run *growth* rather than GDP levels, where effects are theoretically

[1]Indeed, this measure strongly correlates with the technological score of exporters that we build in the construction of the ETI, as shown below.

[2]In addition to Erten et al. (2021) and Kose et al. (2009), the interested reader should consult Quinn & Toyoda (2008) and Quinn et al. (2011) for extensive literature reviews and correlational evidence on the effects of capital account openness.

more likely to manifest. Based on these insights, our contribution provides a tighter identification strategy using the local projection difference-in-difference methodology (Dube et al. 2023) and offers robust findings of the effect of liberalizations on GDP *levels*. Thanks to this tighter identification, we are also able to exhibit clear effects of liberalizations on the volumes of aggregate annual capital flows, which have been notoriously elusive in the literature (see Ostry et al. (2011), Blanchard et al. (2013), Forbes et al. (2015) Magud et al. (2018) and Cerdeiro & Komaromi (2021) for evidence and discussion). Our main focus, however, is on the effects of capital flows on technology adoption, a topic that has received little empirical attention at the aggregate level. Keller (2004) surveyed the seminal literature on the effects of FDI on technology diffusion, concluding that individual case studies provide little evidence of knowledge spillovers, and that positive findings were limited to selected studies employing microdata from the UK and US.[3] More recent empirical papers found positive effects of FDI and financial liberalization on firm-level productivity (Fons-Rosen et al. 2021, Varela 2018) and, using patent data, on innovation (Hou & Xu 2021, Chen et al. 2022).[4] Due to the lack of abundant firm-level and patent data in most emerging and low-income countries, these studies remain limited in their geographical scope. Our contribution consists in extending these findings to a much wider sample of countries, particularly developing and low-income, and considering knowledge diffusion at the country level. Previous to our paper, Alfaro & Hammel (2007) showed that equity market liberalizations lead to an increase in the *volume* of capital inflows. Our analysis complements their insight by focusing on the *quality* of capital goods, defining reform episodes based on overall capital flow restrictions, and extending the country coverage and sample period.

Layout. In the following section we present our proposed measure of technology adoption, how to construct it, validation and stylized facts. Section 3 describes the data and empirical approach we use to measure the effects of external financial liberalization, while we present our main results in section 4. Section 5 presents robustness exercises on our main results, while Section 6 discusses the potential mechanisms behind our results. Finally, section 7 concludes.

[3]This observation is limited to studies measuring knowledge directly. Several earlier papers used indirect evidence of FDI impact on growth to argue in favor of "knowledge spillovers" or "technology transfers" (e.g., Borensztein et al. (1998))

[4]The interested reader should consult Alfaro (2017) and references therein for a comprehensive review of the channels through which FDI translate into higher productivity.

2 Measuring technology adoption

Measuring technology diffusion is generally challenging (Comin & Mestieri 2014), and all the more so for developing and low-income countries that have limited data on patents–because of a dearth of patenting activity or data limitations–and R&D expenditures. PATSTAT, the most comprehensive dataset of worldwide patent bibliographical information, only has consistent coverage for advanced economies and the largest emerging economies.[5] As noted in the literature section, while patents and R&D are adequate measures of invention activity, they only imperfectly measure innovation, which often takes the form of adoption of existing technologies. For these reasons, our measure of technology adoption employs imports of machinery and data on patenting in countries where machines come from. We use patenting in exporting countries to quantify the technology embodied in machines, while imports give us an indication of how much of this technology is actually deployed in the importing country.

2.1 Construction of the Embodied Technology Imports Indicator

Indicator Definition. Our measure, the Embodied Technology Imports indicator (ETI), for country i and goods of type g is defined as:

$$\mathrm{ETI}_{ig,t} = \frac{\sum_{j \in \mathcal{J}_{ig,t}} (M_{ijg,t} \cdot S_{jg,t})}{\sum_j (M_{ijg,t})}, \tag{1}$$

where $\mathcal{J}_{ig,t}$ denotes the set of trading partners of country i in year t for goods of type g, $M_{ijg,t}$ is the dollar value of imports of goods of type g and $S_{jg,t}$ is the relative technology score of country j in year t described below. The ETI is therefore a weighted average of technology scores of import partners of country i for good g. The relative technology score of country j, $S_{jg,t}$, measures the undepreciated patent stock of country j relative to the technology leader at time t. Given a measure of the patent stock for each country, $P_{jg,t}$, we build the technology score as

$$S_{jg,t} = \frac{P_{jg,t}}{\max_j \{P_{jg,t}\}} \times 100. \tag{2}$$

The definitions in (1) and (2) make the measure comparable across countries and periods and allow for a simple interpretation of its levels and changes. The ETI ranges between 0

[5]The coverage for the Spring 2022 edition can be found at https://public.tableau.com/app/profile/patstat.support/viz/CoverageofPATSTAT2022SpringEdition/CoveragePATSTATGlobal. To provide just two examples, Kenya has data for 1972-1984 only and Thailand for 1995-2007 with gaps. R&D data is similarly difficult to obtain due to the lack of long representative firm-level datasets for these countries

and 100 and captures the average technological quality of imports of good g relative to the technological leader at each period in percentage points. An increase in the indicator between period t and $t+1$ means that in period $t+1$ country i is importing a mix of varieties that are closer in quality to those produced by the technology leader in period t. It should be noted that the ETI is scale-free and therefore does not increase mechanically with the volume of imports, rather capturing their composition. Defining the score relative to the leader, rather than assigning an order rank, allows a more precise quantification of the technology leadership of a country relative to using order ranks.[6] We build the stock of patents $P_{jg,t}$ as the sum of all patents for good category g granted up to time t in the patent office of country j, discounted at a 5% annual rate to reflect the duration of patent protection for inventions in many countries including, but not limited to, the United States.[7] As discussed below, we chose to assign patents to the country of the patent authority they are registered in since we are interested in where technologies are produced and likely exported from.

Counting and Attributing Patents. To construct the ETI, we start from the Spring 2022 edition of PATSTAT, a dataset maintained by the European Patent Office (EPO) containing the most comprehensive bibliographical patent information for 90 patent-issuing authorities. We focus on the period between 1947 and 2020 to build our patent measures. These endpoints are chosen to reflect the availability of the Chinn-Ito Index (1971-2020), extended to allow for at least 20 years to build the patent stock available in the first year of the sample and up to four lags of the resulting indicator. For each application authority, we count the families of patents granted in each year.[8] A family collects patent applications referring to the same invention, which can appear at different times in different individual offices. We attribute each patent family to the earliest year that an application appears in a national patent authority and to countries in which it gets registered within three years of the first application date, to account for publication lags.[9] We carry out this attribution in order to identify the countries where the invention is produced and exported from, as applications later than the first few years might just be carried out to protect intellectual property in countries where producers are exporting the invention to, complicating the indicator's

[6]The highest-ranking and the second-highest ranking country might be separated by a just a few patents, while the second- and third-runners might be more technologically distant, but an order rank would consider both these distances the same.

[7]In a previous iteration of the analysis, we obtained similar results building $P_{jg,t}$ as the sum of all the patents registered in country g in the 20 years preceding period t without applying any depreciation, or considering shorter intervals like 10 or 5 years.

[8]We attribute patents registered directly at the EPO (for which the application authority is listed as "EP") to individual European patent offices where the corresponding post-grant fees are paid.

[9]We experimented with attributing the family only to authorities within a year with similar results.

interpretation.

Since patents usually apply to multiple commodities, we employ fractional patent counts to split each patent among the goods it applies to. For each family, we obtain the International Patent Classification at the 4-digit level (IPC4), corresponding to a subclass in the nomenclature of the World Intellectual Property Organization.[10] We then attribute an equal fraction of each patent to each IPC4 class reported by PATSTAT. For example, we count 0.1 patents for each IPC4 code of a patent that is classified as belonging to 10 IPC4 classes. This fractional count allows us to build consistent technology scores at levels of aggregation that are larger than the IPC4 class, where patents that apply to multiple categories would be counted multiple times in proportion to the number of IPC4 codes they refer to.

In order to obtain information on the technology of product classes, we use a crosswalk of IPC4 codes into SITC Revision 2 codes compiled by Lybbert & Zolas (2014) using a natural language processing algorithm on US patents. This crosswalk is probabilistic, resulting in the fractional attribution of each patent classified with an IPC4 code to multiple SITC codes, with a weight that depends on how likely it is that the IPC4 code applies to the product described by the corresponding SITC codes. We chose the SITC Revision 1 classification as it has the longest available period in COMTRADE. We utilize a crosswalk provided by the UN Statistics Division to translate the IPC4 to SITC Rev. 2 crosswalk into an IPC4 to SITC Rev. 1 (SITC1) crosswalk.[11] This final crosswalk allows us to attribute patent counts to individual product categories at the SITC1 5-digit level, which is the lowest level of the product classification.[12] We use this classification to merge PATSTAT and COMTRADE. For the latter, we obtain trade values in USD for SITC1 commodities imported by all countries in our sample as reported by their trade partners, exporter countries.[13] Armed with this data, we compute the ETI following equations (1) and (2) at different levels of the SITC1 code. In our baseline specifications, we manually attribute SITC1 commodities to six large classes for ease of interpretation: "Manufacturing and

[10] This is the third out of five levels in the classification. For example, subclass H01F denotes "Magnets", which belong to the class H01 of "Basic Electric Elements" in section H "Electricity". See https://www.wipo.int/edocs/pubdocs/en/wipo-guide-ipc-2022-en-guide-to-the-international-patent-classification-2022.pdf for more details.

[11] Available at https://unstats.un.org/unsd/classifications/Econ. When Rev. 2 codes are matched to multiple Rev. 1 codes, we partition the probability weights in the IPC4/SITC Rev. 2 crosswalk equally among all the matched subclasses.

[12] Two examples are code 71511, "Machine tools for removing metal" one of the components of 7151, "Machine tools for working metals", and code 69851, "Needles for hand sewing,knitting,netting,etc." as part of 6985, "Pins and needles of iron or steel".

[13] In low-income countries, the trade partners for more technologically advanced goods will likely be advanced economies with higher data collection capabilities than importing countries.

Mining Machinery", "Agriculture Machinery", "Other Machinery", "Other Intermediates", and "Other Equipment", with "Final Goods" as a residual category. We focus primarily on the ETI for machinery as we are interested in technologies that can be used to increase productivity, and not merely final goods for consumption. The category "Other Equipment" includes optical and measurement, medical, and transportation equipment, while "Other Intermediates" includes goods that represent unfinished intermediates.[14]

Baseline: the ETI for Machinery. In what follows, we will focus primarily on the ETI for all machinery, which includes the SITC1 classes we built for "Agriculture Machinery", "Manufacturing and Mining Machinery", and "Other Machinery." For each year, we take the undepreciated fractional count of granted patent families that apply to any of the SITC1 commodities that are relevant to these aggregations to build technology scores of sending countries. Similarly, the weights used to build the ETI are given by the total dollar value of all commodities that fall into one of the three machinery classifications. Our results are robust to using a version of the ETI that weighs families by their size—an ex-ante measure of quality that counts the countries that a patent is registered in—or one using one-year forward citations—an ex-post measure of the quality of the invention. These two measures are highly correlated with our baseline and produce highly similar results, as shown in Appendix B.[15]

2.2 Validation Exercises

We now move to describe the correlation of the ETI and technology scores with measures related to trade and technology diffusion in order to validate our indicator. Namely, we consider exports of machinery, the Economic Complexity Index (ECI) built by Hausmann et al. (2014), and imports and exports of services related to the use of intellectual property (IP) that we obtain from the WTO-OECD Balanced Trade in Services dataset.[16] This dataset is available in two versions, using the 5^{th} edition of the IMF's Balance of Payments Manual for the period 1995-2012 and using the 6^{th} edition for 2005-2021. For the former, we use the item "Royalties and license fees" to measure IP trade flows; for the latter, we employ

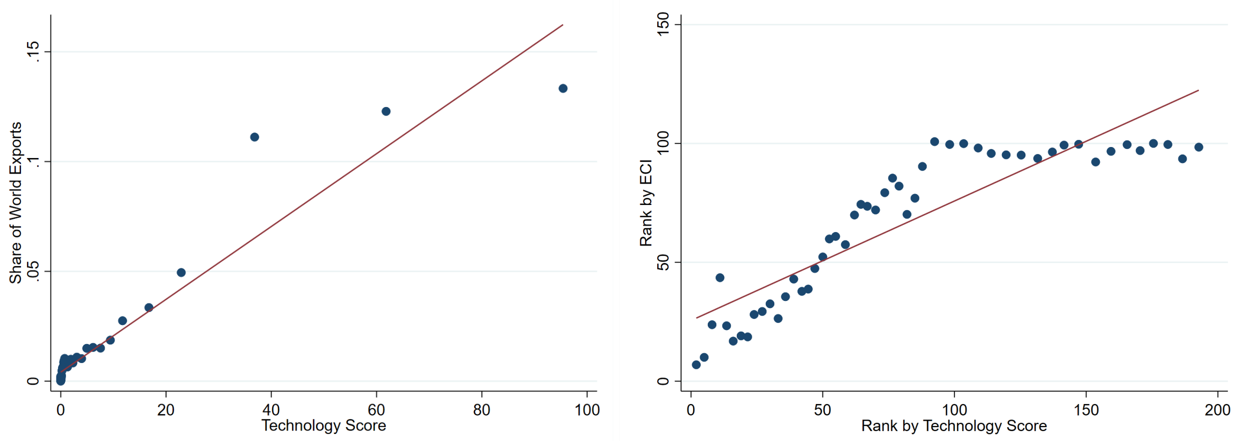
[14]Letting X denote sub-codes, some examples follow. Code 711X, "Power generating machinery, other than electric", is part of "Manufacturing and Mining Machinery" ; code 712X, "Agricultural machinery and implements ", is part of "Agriculture Machinery"; code 714X, "Office Machines" is "Other Machinery"; code 67XX, "Iron and Steel", is classified as "Other Intermediate" as is code 08XX, "Feed. Stuff for animals excl. Unmilled cereals", and code 655X "Special textile fabrics and related products; " 73X, "Transport Equipment" is "Other Equipment" ; agriculture and food products in codes 01XX, "Meat and meat preparations", to 07XX, "Coffee, tea, cocoa, spices & manufacs. Thereof" are classified as "Final Good"

[15]The correlation coefficients for our baseline measure are: 0.884 with the ETI corrected by family size; and 0.899 with the citation-corrected ETI.

[16]The ECI data is from The Growth Lab at Harvard University (2019).

Figure 2: Validation of Technology Scores: Exports and Economic Complexity

(a) World Export Shares, 1970-2020 (b) ECI Rankings, 1995-2020



Note: This figure validates our technology score against other measures of technological leadership. The left panel plots the share of total world exports of machinery for country j against the technology score, $S_{jg,t}$, computed as in Equation (2) for the period 1970-2020. The right panel displays the correlation of country rankings according to the ECI of Hausmann et al. (2014) and rankings according to our technology score for the period 1995-2020, which is covered by the ECI.

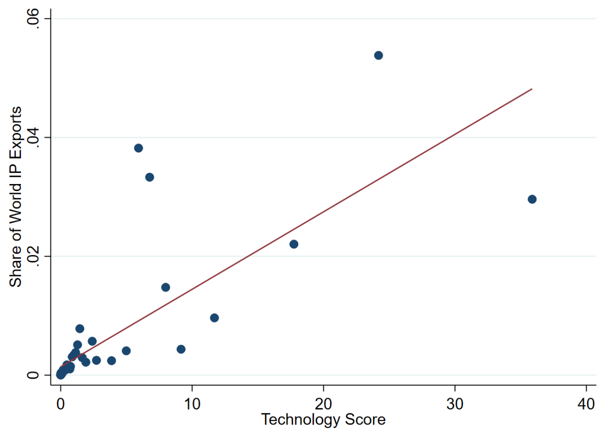
"Charges for the use of intellectual property n.i.e.".[17] The measures are reported in millions of current US dollars. When relevant, we obtain shares of GDP by dividing by nominal GDP in dollars.

The left panel of Figure 2 displays a binned scatter plot of each country's share of world machinery exports against its technology score, $S_{jg,t}$, for g including the SITC1 categories referring to agriculture, manufacturing and mining, and other machinery. The plot reveals a clear correlation between the two measures, which we believe validates our technology scores in two ways. First, the figure shows that goods that are produced by countries with better technology are also in higher demand, suggesting that indeed they may be of higher quality than alternatives. Second, this correlation provides support to our choice of attributing patents to the country of the corresponding patent authority, since exports of technological goods appear to originate primarily from countries with higher rankings. Note that since the graph is a binned scatter plot with 20 bins, the observation that appears extreme corresponds to 5% of the total observations, and as is visible from the graph, results are robust to dropping all observations that have a share of world exports higher than 0.05. For this and the following figures, we also checked that the same relations

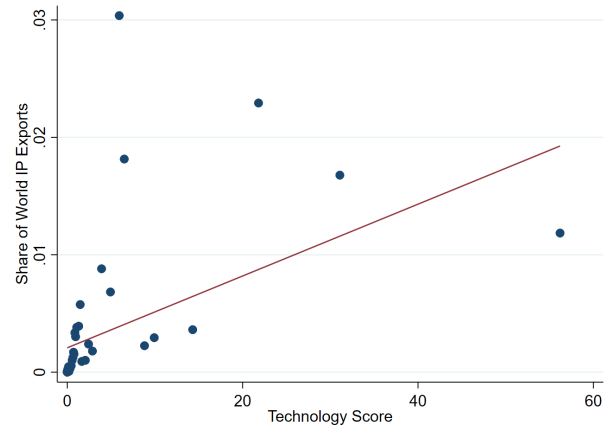
[17] The datasets can be downloaded in bulk at https://www.wto.org/english/res_e/statis_e/trade_datasets_e.htm. We use codes S266 and SH for the BPM5 and BPM6 versions, respectively.

Figure 3: Binscatter of Exports of IP to the World versus Technology Rankings

(a) BPM 5, 1995-2012



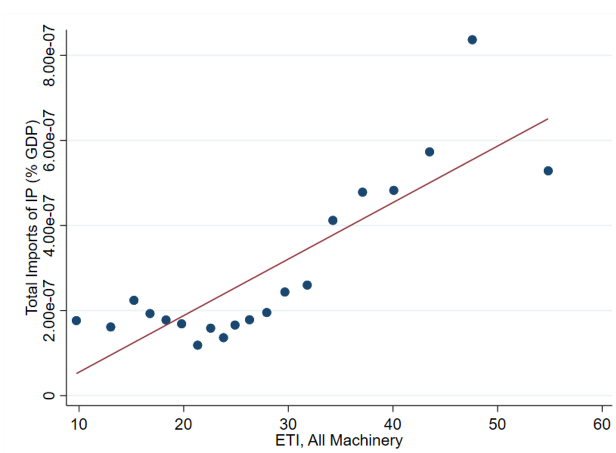
(b) BPM 6, 2005-2021



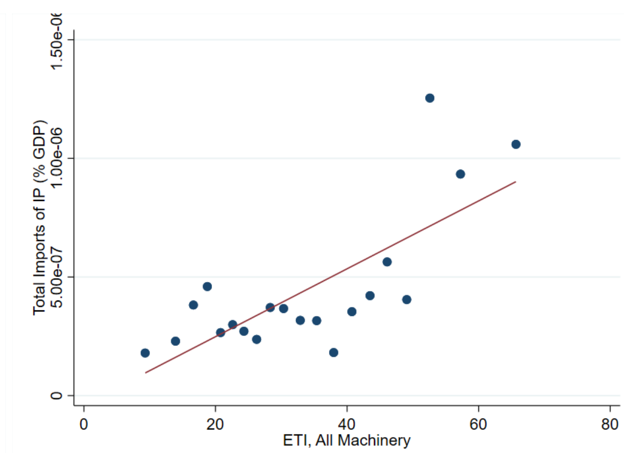
Note: This figure plots share of world exports of intellectual property services (codes S266 and SH for the BPM5 and BPM6 versions, respectively) from the WTO-OECD BATIS data against technology scores for machinery, $S_{jg,t}$, computed as in Equation (2). Observations for US and Japan are excluded, with a full plot presented in Appendix A.

Figure 4: Binscatter of Imports of IP from the World versus Machinery ETI, EMDEs

(a) BPM 5, 1995-2012



(b) BPM 6, 2005-2021



Note: This figure plots imports of intellectual property services (codes S266 and SH for the BPM5 and BPM6 versions, respectively) form the WTO-OECD BATIS data as a percentage of GDP against the ETI for all machinery, $ETI_{ig,t}$, computed as in Equation (1).

hold when considering narrower commodity groupings, for example restricting to only agriculture or manufacturing machinery (these results are available on request). The right panel of Figure 2 contains a binned scatter plot of country rankings according to Hausmann et al. (2014) and rankings when we sort countries based on our technology score. The correlation between the two rankings is 0.72 and highly significant. Note that the ECI is constructed to capture the technological sophistication of all exports of each country, not just machinery. This high correlation therefore comforts us that countries that we consider advanced according to our technology score also tend to export more advanced goods in general, which is crucial to the interpretation of our measure, the ETI.

Figure 17 paints a similar picture for the world share of IP exports, both for the measure built according to the BPM 5 for 1995-2012 and for the measure employing BPM 6 definitions. As above, a higher technology score is associated with higher exports of intellectual property services, suggesting that countries that are ranked higher according to our measure, $S_{jg,t}$, indeed have a leading role in exporting IP. These graphs already exclude observations for the US and Japan, the inclusion of which would dwarf other observations. We present the full plots, which display even stronger correlations, in Appendix A. Figure 4 displays binned scatter plots of total IP imports as a percentage of the importing country's GDP against the ETI for all machinery. The strong positive correlation highlights that a higher ETI is associated with larger volumes of intellectual property transfers. It could be that imports of higher-technology machines bring with them the need to acquire new intellectual property for their operation or that technology upgrading occurs at the same time as higher-tech imports. Whichever the reason for the correlation, this finding suggests that the ETI is associated with the knowledge flows and the adoption of new technologies which we wish to study. [18]

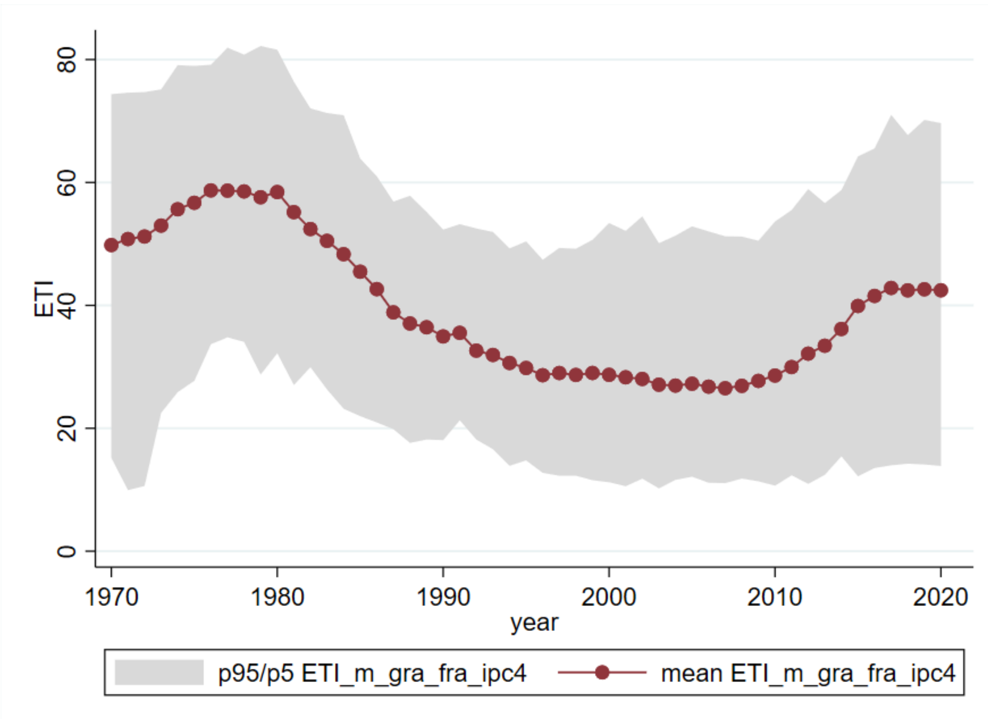
2.3 Stylized Facts on the ETI

Figure 5 depicts the evolution of our baseline ETI measure for all machinery for EMDEs. The line represents the average ETI and the shaded area the range between the 5^{th} and 95^{th} percentile. Over our sample period, the indicator remained relatively stable around an average of 40, with a gradual decrease over the 1980 decade and a more recent increase in the 2010 decade.

Fact 1: There are long-run trends in technology adoption driven by technology leaders activity. The long-run changes observed in 5 result from the large increase in patenting

[18] We verified that a similar pattern holds also for year-on-year changes, although the correlation is somewhat attenuated. We also checked that the correlation holds when considering narrower sets of goods. These additional results are available on request.

Figure 5: The Embodied Technology Imports Indicator



Note: This figure presents the cross-country average of the ETI measure for all machinery (Agriculture, Manufacturing and Other Machinery) for EMDEs over the period 1970-2020 together with the fifth and ninety-fifth percentile.

in Japan during the 1980s which was not followed by an equally large increase in the imports of technologies from Japan across all countries, and the more recent increase is related to the increase in patenting activity in China which occurred concurrently with the large increase in worldwide trade with China. Indeed, while the ETI always ranges between 0 and 100, it measures the technology content of imports *relative* to the country with the highest stock of relevant granted patents at that point in time. Therefore, the index can drop across the board when the technology leader has far more patents than followers in a certain period, since by construction this depresses every other country's score as computed from Equation (2). For this reason, we recommend the inclusion of time fixed-effects to account for the long-run trends across countries.

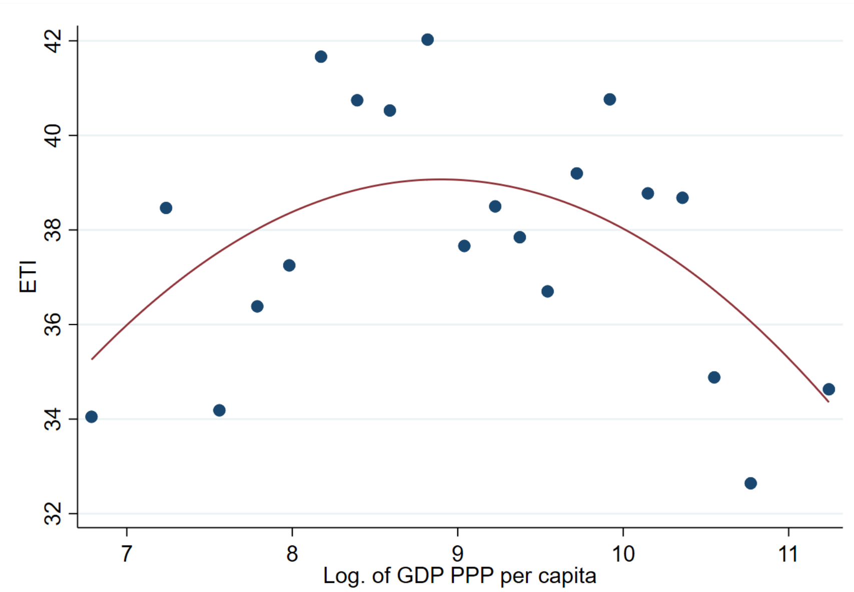
Fact 2: There is an inverse U-shaped relationship between the ETI and GDP per capita. Figure 6 displays the inverse U-shaped relation that emerges from a binned scatter plot of the ETI against PPP real GDP p.c.. We interpret this relation as stating that, along the development path, countries first import and adapt foreign technologies with increasing sophistication and then move to produce their own advanced machinery, leaving them to import only less sophisticated machinery than what they produce.[19] Accordingly, the ETI is an adequate measure of technology diffusion only in a developing country context. Indeed, the relation between ETI and GDP PPP p.c. is linear and upward-sloping when restricting to EMDEs (available on request).

Fact 3: Growth in the ETI is followed by GDP growth in EMDEs. Increases in the ETI usually precede growth in real GDP PPP p.c., suggesting that the technological upgrading encapsulated by our measure leads future productivity improvements. Figure 7 reports a binned scatter plot average five-year GDP PPP p.c. growth against lagged five-year ETI growth. We take these averages to absorb short-term fluctuations that are pervasive in both series, and plot data points after residualizing by five-year fixed-effects to capture time-specific shocks.

Fact 4: The ETI is positively correlated with higher external financial openness. Figure 8 displays the correlation of the ETI with the level of external capital openness obtained in the same manner as for GDP growth in Fact 3. In the cross section of EMDEs, higher levels of the Chinn-Ito index correspond to higher levels of the ETI, suggesting that technology adoption comes hand-in-hand with higher external finance openness. The rest of the paper examines this fact in depth.

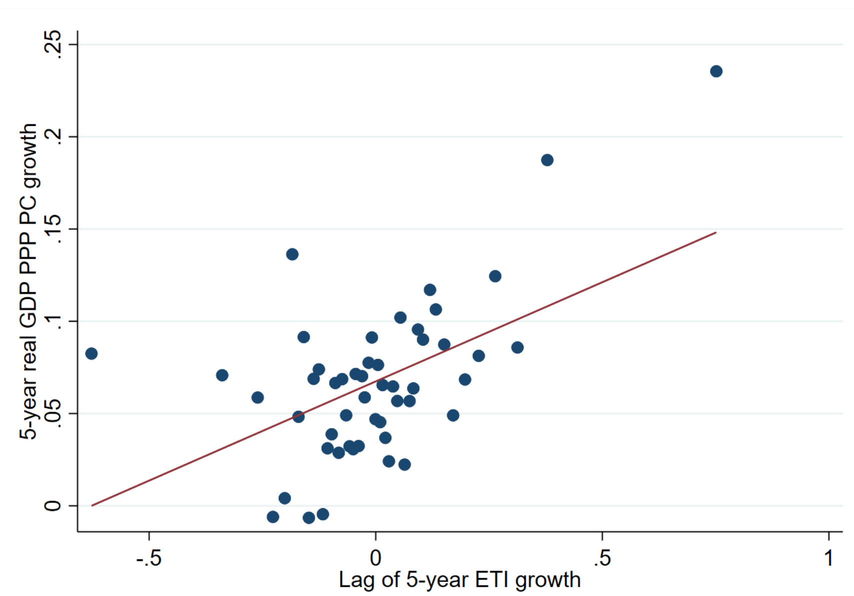
[19]See Choi & Shim (2023) for evidence on this process for the case of South Korea.

Figure 6: The Inverse-U Relation of the ETI with per capita PPP GDP



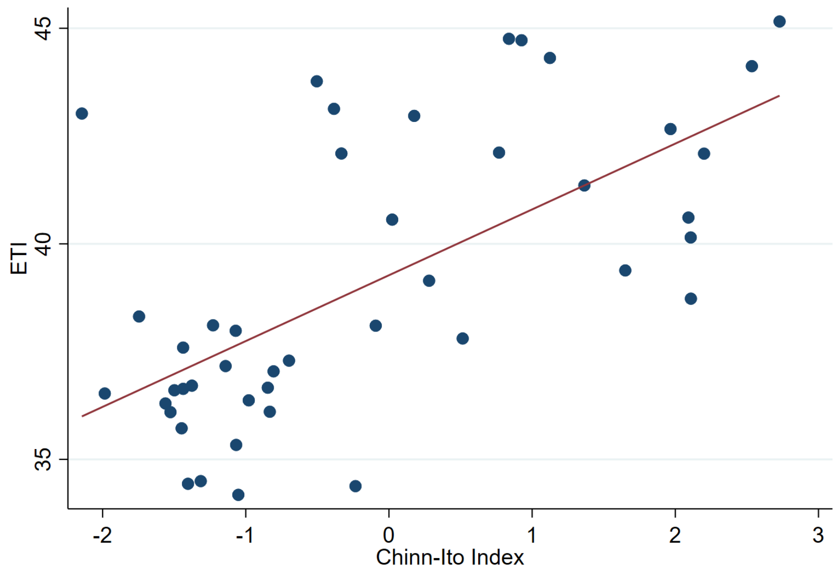
Note: This figure presents a binned scatter plot of five-year averages of the ETI index against five-year averages of the logarithm of GDP per capita at purchasing power parity exchange rates. The line is obtained by fitting a quadratic polynomial.

Figure 7: GDP PPP per Capita and Past ETI Growth in EMDEs



Note: This figure presents a binned scatter plot of five-year changes in the logarithm of GDP per capita at purchasing power parity exchange versus the five-year change in the logarithm of the ETI index in the previous five-year period. Fixed-effects for five-year periods are partialled out.

Figure 8: ETI and External Finance Openness in EMDEs



Note: This figure presents a binned scatter plot of the average ETI against the average Chinn-Ito index for five-year periods. Fixed-effects for five-year periods are partialled out.

3 Data and Methodology

In this section we describe the data and methodology used for analyzing the effects of capital flows liberalization.

3.1 Data

Capital flows liberalization episodes. We focus on *de jure* external financial liberalization, which consists in the removal of legislated barriers to international capital flows. We define liberalization episodes using the Chinn-Ito index (Chinn & Ito 2008), which provides a unified numerical indicator of the restrictions to capital flows described in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). In particular, the index aggregates four dummy variable encoding the presence of multiple exchange rates, restrictions on current account transactions, restrictions on capital account transactions, and the surrender of export proceeds. Chinn & Ito (2008) assign weights to these four components through principal component analysis.[20] The resulting index

[20]The measure does not focus exclusively on capital account restrictions in an effort to capture other hurdles on free capital flows, as well as the intensity of capital controls. For example, the authors note that "countries that already have closed capital accounts might try to increase the stringency of those controls by imposing other types of restrictions (such as restrictions on current account and requirements for surrender of trade proceeds) so that the private sector cannot circumvent the capital account restrictions." A similar point is made by Erten et al. (2021) who note that restrictions on the use of foreign currency "do not officially count as capital controls but have the side effect of applying to most transactions with foreigners who

is available for an unbalanced panel of 181 countries in the period 1971-2020 and ranges between -1.93 and 2.31, with higher values denoting more *de jure* openness to capital flows (less restrictions). We chose this indicator over available alternatives due to its wider coverage both across countries and time. Indeed, our empirical strategy and our focus on technology adoption requires a relatively long time period and a wide sample of developing and low-income countries. Several other measures of capital openness, while very detailed in their content (Schindler 2009, Fernández et al. 2016, Jahan & Wang 2016, Horn & Narita 2021) cover only the period after 1995, and for the most part few EMDEs. The indicator built by Quinn & Toyoda (2008) has the closest coverage to the Chinn-Ito index, especially when it comes to the time dimension. However, the KAOPEN series has 2321 additional country-year observations referring to developing and low-income countries, which make up 38% of all observations for these economies in our analysis.

We identify capital flow liberalization episodes as country-year pairs that see an increase in the Chinn-Ito index greater than or equal to the 95th percentile of observed year-on-year changes over our sample of interest. This corresponds to a year-on-year change in KAOPEN of 0.254. [21] We further restrict attention to "clean" reform episodes, defined as those that do not see other change in KAOPEN in the previous five years. This restriction is motivated by the local projection difference-in-difference methodology that we employ (Dube et al. 2023), described in detail in Section 3.2. As discussed below, this approach accurately estimates the dynamic effects of liberalizations if the effects of these reforms on outcomes of interest become constant for time horizons of five or more years after an increase in KAOPEN.

This episode definition identifies 123 capital flow liberalization events (90 of which in EMDEs), which see an average increase in KAOPEN of 0.96, and a median change of 1.07, corresponding to the 97^{th} percentile of year-on-year changes in the full sample.[22] Figure 9 represents the resulting sample of episodes graphically. The full length of the bars provides a count of countries that register an increase in KAOPEN of at least 0.254 in each year, while the light blue portion counts the episodes that are considered clean events according to our definition. Several features stand out. First, episodes of liberalization tend to be clustered around specific years, with the vast majority occurs in the 1990 and 2000 decades. Second, episodes are often part of longer periods of liberalization for individual

typically transact in foreign currency."

[21] In practice, this choice of threshold includes all episodes with an increase in the index bar one, as almost 90% of the observations in the sample see no year-on-year change. We round the Chinn-Ito index at the third decimal digit. This bunches together some KAOPEN changes differing at the seventh digit, which we believe to be a result of small rounding errors.

[22] We also explored a specification requiring no KAOPEN changes in the 10 periods preceding reform episodes, with similar qualitative findings.

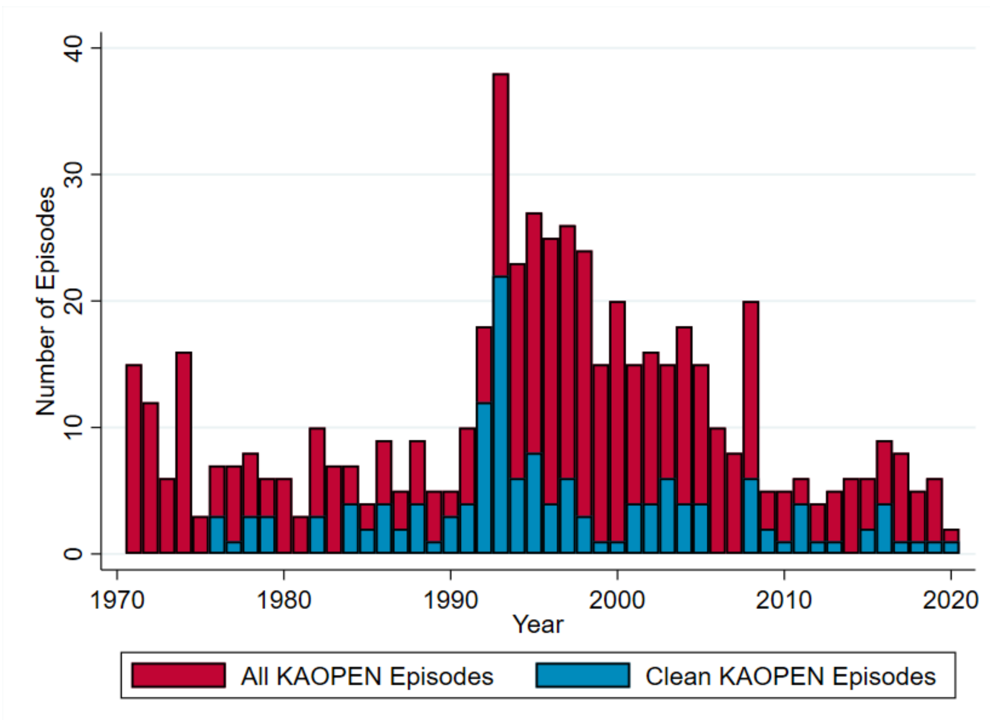
countries. In light of the above discussion, the episodes included in the red portion of the bar are instances that saw another change in the KAOPEN measure in the previous five years. In part, this is a feature of the Chinn-Ito index, which among its components includes a moving average of the dummy denoting the presence of restrictions on capital account transactions, but more in general it appears to be the case that capital controls are gradually lifted, resulting in multiple staggered increases in the KAOPEN index. It is important to note that the episodes in the red portion of the bars are not always discarded. Instead, their effects might be part of previously occurring "clean" episodes. In other words, episodes that are not considered to be clean are never part of the control group, and they are not to be considered as the start of an entirely new episode, but they are included in the sample of treated units for the estimation of dynamic effects when appropriate. Note that we consider the first five years after a country joins the panel as being unclean, since we cannot exclude that years outside the sample coverage saw KAOPEN changes. This is clearly visible in the figure, where the first five years only include red bars.[23] We report specific examples as well as the full set of episodes in Appendix A.

Trade Restrictions. To account for episodes of trade liberalization, we make use of the MATR (Measure of Aggregate Trade Restrictions) built by Estefania-Flores et al. (2022), which also builds on the IMF AREAER dataset but focuses on measures that restrict trade rather than purely financial flows. This measure shares some of its components with the Chinn-Ito index, since the latter includes current account restrictions and requirements for surrender of trade proceeds as discussed above. We include the trade components of the MATR as a control to ensure that our results on technology imports are not solely driven by increases in trade openness. In this respect, as noted in section 2, the ETI does not respond mechanically to changes in trade volumes since this indicator is scale-free. Instead, the ETI varies when the composition of trade partners for specific goods changes. Therefore, as long as trade restrictions are similar across partners, changes in the MATR should not directly mechanically affect the ETI. In terms of coverage, the MATR is available for 157 countries and for all years in our sample up to 2019.

Macroeconomic data. For the remaining macroeconomic data, we use data from the IMF World Economic Outlook. We pull data for real GDP per capita in PPP terms, imports and exports of goods and services in constant dollars, as well as several measures of capital flows. We consider FDI inflows and outflows, overall capital inflows and outflows, portfolio inflows and outflows and "other investment" inflows and outflows. All these

[23] In a previous iteration, we included episodes at the beginning of each country's panel among clean events, obtaining qualitatively similar results.

Figure 9: Episodes of Capital Flow Liberalization



Note: This figure displays the number of events of capital flows liberalization occurring each year (positive changes in KAOPEN over 0.254). The full length of the bars represents the total number of episodes for each year, while the lighter blue portion represents the episodes that we include in our baseline analysis.

measures are highly volatile, making estimates based on yearly flows noisy. To tackle this issue, we consider effects on lifetime cumulative capital flows, which provide smoother series and a more sensible benchmark for the pre-period compared to volatile yearly flows in $t-1$. Thus, coefficients β_h from the LP-DiD specification identify the total additional capital flows received over horizon h from liberalization events compared to control countries. We also take the inverse hyperbolic sine transformation to deal with the high cross-sectional dispersion in cumulative flows, a monotonic transformation with similar curvature to the natural logarithm but with domain over the entire real line, and concave for positive values.

3.2 Empirical approach

We use a local projection difference in differences approach (LP-DiD) to estimate the effects of capital flows liberalization. Our specification adapts equations (24) and (25) in Dube et al. (2023), which apply to cases where multiple treatments can occur for the same unit (treatment is "non-absorbing"):

$$y_{i,t+h} - y_{i,t-1} = \beta_h \Delta D_{i,t} + \delta_t^h + \sum_{j=1}^{p} \gamma_j^h y_{i,t-j} + \sum_{j=1}^{p} \boldsymbol{\eta}_j^{h,\prime} \mathbf{x}_{t-j} + \varepsilon_{c,t}^h. \tag{3}$$

The dependent variable is the cumulative growth in the outcome variable, y, between period $t-1$ and period $t+h$. The main dependent variable, $D_{i,t}$ is a dummy variable indicating that country i undergoes a liberalization episode at time t, while controls include time fixed effects, δ_t^h, pre-treatment lags of the change in the outcome variable, and a vector of other pre-determined control variables, $\mathbf{x}_{t-j}$. The estimation sample is restricted to the set of countries that satisfy:

$$\begin{cases} \text{liberalizations} & \Delta D_{i,t} = 1; \quad \Delta D_{i,t-j} = 0 \; \forall j \in \{1, \ldots, L\}, \\ \text{clean controls} & \Delta D_{i,t} = 0; \quad \Delta D_{i,t-j} = 0 \; \forall j \in \{1, \ldots, L\}. \end{cases} \tag{4}$$

In other words, for treatment occurring at time t, no unit included in the analysis should have been treated at any of the preceding L periods. Thus, relative to a standard local-projection specification, LP-DiD ensures that no unit that is treated or included in the control group is still experiencing delayed treatment effects from liberalization events occurring any period between $t-1$ and $t-L$. Dube et al. (2023) show that coefficients $\hat{\beta}_h$ recover the causal effects of a change in treatment $D_{i,t}$ as long as true treatment effects β_h are constant after L periods after the event occurs, $\beta_h = \beta_{h+s}$ for all $s > 0$ and $h \geq L$. The findings in de Chaisemartin & D'Haultfœuille (2020) and Goodman-Bacon (2021) demonstrate that estimating (3) without this sample restriction leads to biased coefficients, as including previously treated units in the control group implies that delayed treatment effect dynamics are effectively subtracted from the estimated coefficients $\hat{\beta}_h$. Simply put, some of the units for which $\Delta D_{i,t} = 0$ will have, e.g., $\Delta D_{i,t-L} = 1$, which will make them inadequate comparisons as long as the effect of $\Delta D_{i,t-L}$ is still increasing at time t. This is because the coefficient $\hat{\beta}_h$ is essentially taking a difference between the average outcome of treated units and the average outcome of control units. If the latter is polluted by some treatment effects resulting from previous treatments, the estimated coefficients will be inevitably biased. At the same time, if we impose $D_{i,t-L} = 0$ for L high enough, we ensure that effects from previous treatments have stabilized and are therefore subtracted out when taking the difference between $y_{i,t+h}$ and $y_{i,t-1}$.[24] We dub L the "number of stabilization periods," as it represents the number of years required for treatment effects on the outcome variable $y_{i,t+h}$ to stabilize. Accordingly, we choose L so that estimated treatment effects do not change between period $t + L$ and subsequent periods in a statistical sense, which we determine by checking that estimated coefficients $\hat{\beta}_{L+s}$ fall in the 90% confidence interval for $\hat{\beta}_L$.[25] We choose $L = 5$ by analyzing the time path of estimated coefficients under different assumptions on the number of stabilization periods and several outcome variables. The graphs reported in the following section are consistent with this assumption, with estimated coefficients for horizons between 5 and 10 periods after liberalizations statistically indistinguishable from each other.

The outcome variables are: the logarithm of GDP at purchasing power parity (PPP) exchange rates per capita (p.c.), the inverse hyperbolic sine of cumulative capital inflows (total flows, FDI, portfolio, and other investment), and the logarithm of our measure of technology adoption. We adopt these variable transformations to allow for easy interpretation of the result as percentage cumulative increase in the outcome at the relevant horizon. When using the inverse hyperbolic sine transformation, we report the outcome's cumulative percentage increase in a neighborhood of the sample average. Motivated by our findings on treatment and control balance below, we include two lags of growth in

[24]If treatment effects are not dynamic, that is, $\beta_h = \beta_{h+s}$ for all s, or they are dynamic but do not change with t, then the estimated $\hat{beta}_h$ coefficients are the same as those obtained from the simple static two-way fixed effects regression:

$$y_{i,t} = \alpha_i + \delta_t + \sum_h \beta_h \Delta D_{i,t-h} + \sum_{j=1}^{p} \gamma_j^h y_{i,t-j} + \sum_{j=1}^{p} \boldsymbol{\eta}_j^{h,\prime} \mathbf{x}_{t-j} + \varepsilon_{c,t}^h. \tag{5}$$

Since the LP-DiD is in differences, unit i fixed effects cancel out.

[25]In most instances, the number of treated units drops dramatically for large number of periods after treatment, so we check that this condition holds up to the post-treatment period that has a comparable number of observation as that available at lag L.

GDP PPP p.c. as a control in all regressions.

Throughout, we employ robust standard errors clustered at the country level. The inclusion of lags of the dependent variables might raise some concerns that our estimates suffer from Nickell (1981), for which we present an alternative specification in Appendix B employing Arellano & Bond's (1991) methodology. In the same Appendix, we also report our main estimates with Driscoll & Kraay (1998) standard errors to account for cross-sectional correlation.

3.3 Treatment and Control Balance

We compare treated countries with never-treated countries along several dimensions of interest, with an eye to detect unconditional violations of the parallel trend assumption required by our empirical strategy. Among the variables we analyze, we find significantly different trends only in GDP PPP per capita and capital openness. These differences motivate our choice of GDP PPP per capita growth and the clean control condition (4). The latter eliminates pre-treatment differences in the behavior of KAOPEN across treatment and control units in our regression sample, while the former allows us to match observations by their past growth. As a result of these precautions, we do not detect significant differences in pre-trends across treatment and control units *conditional on covariates*. Appendix A.3 provides a balance table and the details of its construction.

4 Main Results

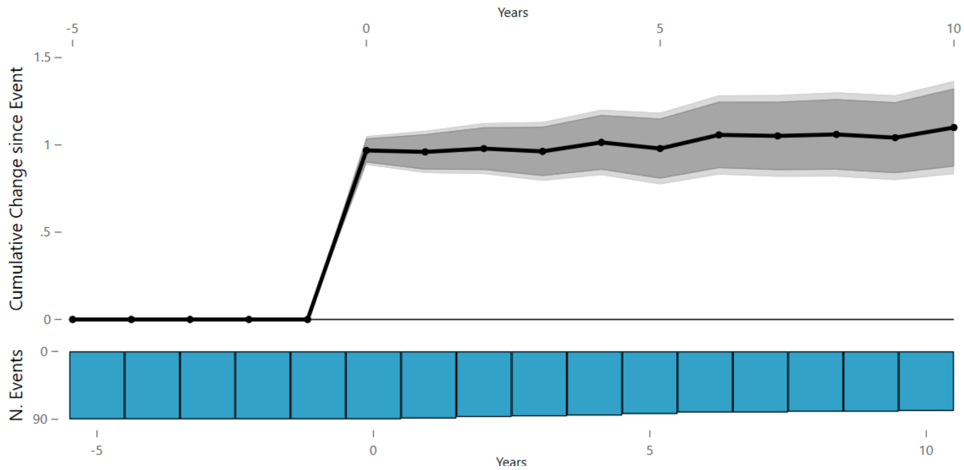
This section presents our LP-DID estimates for three sets of outcome variables: capital flows, technology adoption, and output. Out of the 123 events identified in Section 3, 90 correspond to liberalizations in EMDEs. Figure 10 presents the cumulative response of the Chinn-Ito index to these episodes for EMDEs. After the events we study, KAOPEN exhibits a permanent increase of about one unit, equivalent to almost three standard deviations of the KAOPEN changes using the full sample, and 2.8 standard deviation of changes within EMDEs. On average, the events we study are not followed by a reversal and represent a large change in the measure of capital account openness. There are no significant pre-event trends in the ten years before the episodes.[26]

4.1 Capital Flows

Our first set of results relate to the effect of financial liberalization on capital flows themselves. As discussed in the literature review, findings of systematic effects on capital flows have been elusive, in part due to *de jure* capital account openness not necessarily reflecting how reforms are made operational, but also potentially due to the way responses

[26] For the five years before the events this is by construction.

Figure 10: Cumulative Response of the Capital Account Openness Index



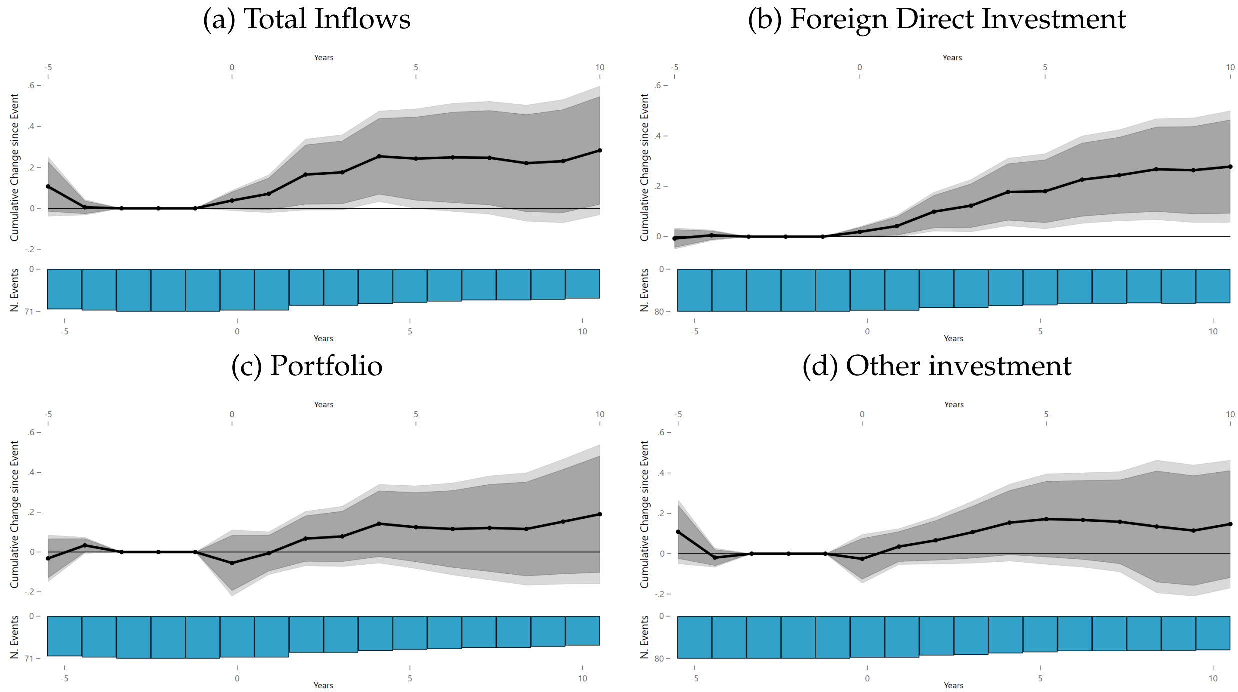
Note: this figure displays the cumulative response of the capital account openness measure KAOPEN to the capital account liberalization episodes defined in section 3. For each horizon h since the liberalization period (Years = 0), the black solid line plots the cumulative response and corresponds to the coefficient β_h from equation (3) with five stabilization lags and no additional controls. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using robust standard errors clustered at the country level. Bars display the number of events used to compute the response at each horizon.

to liberalization events have been measured in the past. In particular, several studies have employed conventional event-study methods or distributed-lag specifications which are not well-suited to account for repeated treatments that are typical of financial liberalizations.[27] We focus on gross capital inflows, defined as liability flows net of repayments. For all capital flow variables, we express them in billions of US dollars and apply an inverse hyperbolic sine transformation to the cumulative lifetime total of capital flows at time t.

Figure 11 displays the response by type of capital flows. Starting from the top left panel, we find that capital account liberalizations increase transformed lifetime gross capital inflows by 0.24 over the medium term and 0.28 in the long-run. This represents 0.9 to 1.1 times the standard deviation of changes in transformed capital flows for all EMDEs and 1.1 to 1.3 times the average within country standard deviation of transformed capital flows changes. These are relatively large changes, in part because they incorporate both extensive and intensive margins. Our estimated effect is equivalent to an increase of 28% and 33% of lifetime capital flows over the medium and long-term respectively. The remaining panels show that the increase in lifetime capital flows received is driven by Foreign Direct Investment (FDI) flows. Lifetime FDI inflows increase by 21% five years

[27] As explained in Section 3.2, using these methods would include some previously treated units in the control group, with the likely effect of biasing estimated treatment effects toward 0. This is exactly what we see if we set the number of stabilization lags to 0 in our analysis. Results available on request.

Figure 11: Cumulative Response of Lifetime Gross Capital Inflows



Note: This figure displays the cumulative response of the inverse hyperbolic sine of lifetime gross total, foreign direct investment, portfolio, and other investment inflows in billions of US dollars, to the capital account liberalization episodes defined in section 3. For each horizon h since the liberalization (Years = 0), the black solid line plots the cumulative response estimated by the coefficient β_h in equation (3) with five stabilization lags, two lags of log GDP, and two lags of the outcome variable. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using robust standard errors clustered at the country level. Bars display the number of events used to compute the response at each horizon.

after the event, while the increase in other investment flows and portfolio flows is not statistically significant.[28]

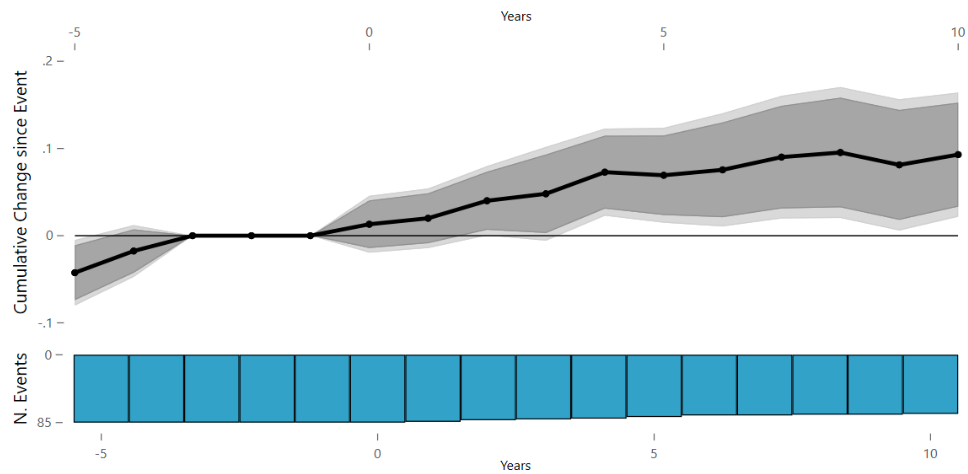
4.2 Technology adoption

Our main result concerns the effect of capital account liberalization on technology adoption. We find that the ETI indicator increases over the medium and long term after capital account liberalization events, as shown in Figure 12. The ETI increases by 7% five years after the event and 9% in the long-run. This effect is equivalent to 30% to 40% of the standard deviation of the ETI changes for all EMDEs over the sample period analyzed and to 45% to 57% of the average of the within country standard deviation of ETI changes. Capital account liberalization episodes are followed by larger inflows of capitals, particularly through FDI, and by an improvement in the technology embodied in imports. Appendix B

[28]We obtain qualitatively similar results using the period by period inflows as well as using a natural logarithm instead of the inverse hyperbolic sine transformation. Results and are available upon request.

presents further results that support the improvement in technology adoption, by using as outcome variables the import of IP and alternative ETI definitions (both at the level of aggregation of goods considered as well as how patents are counted). Our results on capital flows suggest that this improvement in technology is related to the increase in foreign direct investment.

Figure 12: Cumulative Response of Technology Adoption

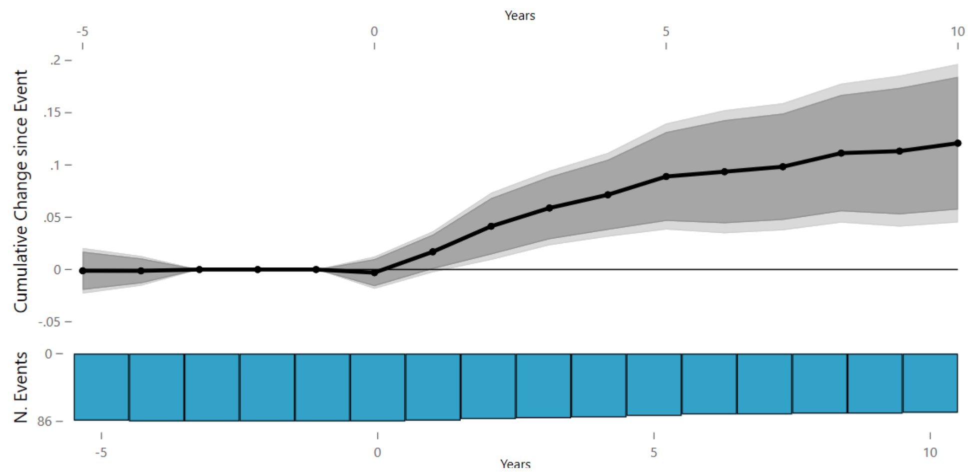


Note: this figure displays the cumulative response of the natural logarithm of the Embodied Technology Imports (ETI) Indicator to the capital account liberalization episodes defined in section 3. For each horizon h since the liberalization period (Years = 0), the black solid line plots the cumulative response and corresponds to the coefficient β_h from equation (3) with five stabilization lags, two lags of log GDP, and two lags of the outcome variable. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using robust standard errors clustered at the country level. Bars display the number of events used to compute the response at each horizon.

4.3 Output

Finally, we reexamine the effect of external financial liberalization on output as shown in Figure 13. We find that financial liberalization has a positive impact on PPP Real GDP per capita levels over the medium to long-term. Output increases by 9% and 12% five and ten years after the event respectively. This is equivalent to 1.3 and 1.8 standard deviations of GDP changes in the sample and to 2.5 and 3.4 of the average within country standard deviation of GDP changes. Our tighter identification strategy allows us to find this positive and significant effect in output levels (as conjectured by Henry 2007). Our results provide suggestive evidence that the increase in capital flows allows for investment in more modern technology and a consequent increase output.

Figure 13: Cumulative Response of Output



Note: this figure displays the cumulative response of the natural logarithm of real GDP per capita in PPP dollars to the capital account liberalization episodes defined in section 3. For each horizon h since the liberalization period (Years = 0), the black solid line plots the cumulative response and corresponds to the coefficient β_h from equation (3) with five stabilization lags and two lags of log GDP. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using robust standard errors clustered at the country level. Bars display the number of events used to compute the response at each horizon.

5 Robustness and Other Results

As noted in the literature (see, e.g., Furceri et al. 2019), capital account liberalization episodes could be correlated with unobserved factors that also drive outcomes such as GDP. For example, countries might choose to liberalize the capital account when GDP is weakening or in tandem with other structural reforms, or the quality of government/institutions could drive both reforms and GDP. In our main specification, we take several steps to mitigate this concerns. First, we present several lags preceding the events to allow for the inspection of pre-treatment differences between treatment and control groups, which are never systematic after conditioning for lagged GDP growth and the dependent variable of interest. The inclusion of lagged variables like GDP growth and the corresponding outcome variables also control for expectations on those variables, insofar as those expectations are formed based on past outcomes. We perform several robustness exercises to address omitted variable bias and other endogeneity concerns. This section present the main exercises related to omitted variable bias, while Appendix B presents results for alternative assumptions on the estimation method. In particular, we use Arellano & Bond's (1991) methodology to show that the inclusion of lags of the dependent variable does not cause our estimates to suffer from Nickell's (1981) bias, and employ Driscoll &

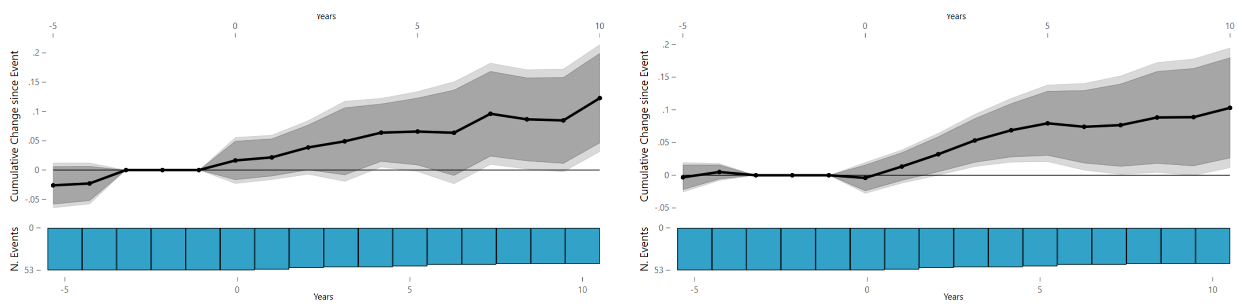
Kraay (1998) standard errors with unchanged results.

5.1 Simultaneous Reforms

If governments implement external financial liberalization reforms as part of a broader package of reforms, the results presented in Section 4 are not solely driven by the financial liberalization, but by the package as a whole. We use the MATR indicator to exclude from the episodes defined in Section 3 those that are accompanied by an ease in trade restrictions.[29] Data availability for this indicator reduces the number of events by 40%, and the rest of the overall sample by about 13%. Figure 14 summarizes the results. Our results hold up to this narrower definition of events. We find larger effects on capital flows and a similar effect on technology adoption and output.

Figure 14: Cumulative Response to Narrower Liberalization Episodes

(a) Technology Adoption (b) Output



Note: this figure displays the cumulative response of the natural logarithm of the Embodied Technology Imports (ETI) indicator, and the natural logarithm of real GDP per capita in PPP dollars to the capital account liberalization events. Events are defined based on changes in the KAOPEN indicator as defined in section 3 and exclude events that also ease trade restrictions according to the pure trade components of MATR. For each horizon h since the liberalization period (Years = 0), the black solid line plots the cumulative response and corresponds to the coefficient β_h from equation (3) with five stabilization lags, two lags of log GDP, and two lags of the outcome variable. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using robust standard errors clustered at the country level. Bars display the number of events used to compute the response at each horizon.

5.2 Full set of controls

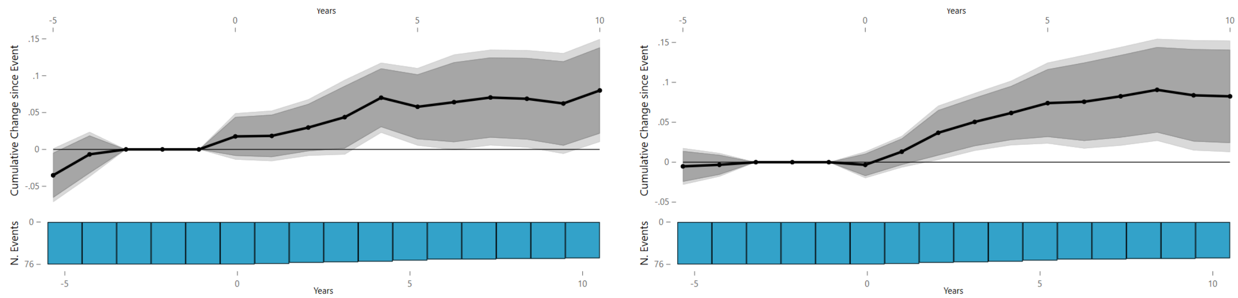
We also consider a larger set of controls that aim to remove the effect of other macroeconomic conditions affecting the outcome variables of interest. Overall, we condition on IMF programs, trade openness, and changes in net capital flows, together with the lags of output growth and of the dependent variable. Including all these controls reduces the pool of events by 25%, which helps explain the less precise estimates. Overall the results

[29]This is constructed as the sum of the measures included in items VII and VIII of the AEREAR. See Estefania-Flores et al. (2022) for more details.

obtained are in the same direction, magnitude and significance as under our baseline both for technology adoption and GDP (Figure 15).

Figure 15: Cumulative Response (Full Set of Controls)

(a) Technology Adoption (b) Output



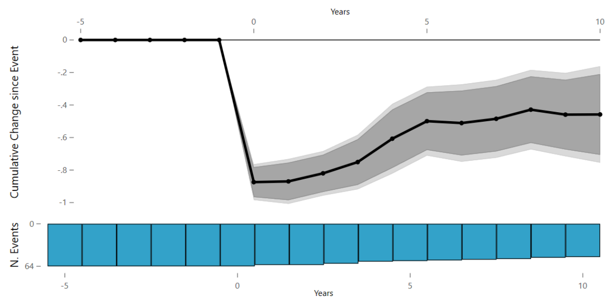
Note: this figure displays the cumulative response of the natural logarithm of the Embodied Technology Imports (ETI) indicator, and the natural logarithm of real GDP per capita in PPP dollars to the capital account liberalization episodes defined in section 3. For each horizon h since the liberalization period (Years = 0), the black solid line plots the cumulative response and corresponds to the coefficient β_h from equation (3) with five stabilization lags, two lags of output growth, two lags of the outcome variable, two lags of trade openness defined as imports and exports of goods over GDP, two lags of the change in the asine transformation of net capital flows, and three lags of a dummy variable that indicates whether the country has an ongoing IMF program of any type. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using robust standard errors clustered at the country level. Bars display the number of events used to compute the response at each horizon.

5.3 Capital Account Restrictions

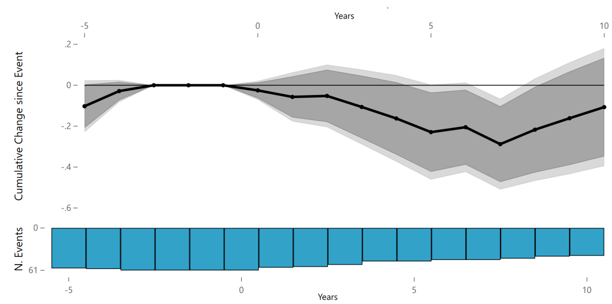
We also consider the case of capital account restrictions. Since these restrictions tend to take place when there are stability concerns, we include the full set of controls from the previous subsection. As shown in Figure 16, panel (a), while the initial size of the restrictions tends to be similar to that of liberalizations, these episodes are partially reversed within five years. While we do not find a significant effect on either FDI inflows or technology adoption, there is a significant decrease in portfolio inflows and in GDP, the latter being comparable to the increase found after liberalizations. This exercise shows that capital account restrictions do not mirror liberalization episodes and affect output through different channels. In particular, the constraints imposed during these type of episodes don't seem to affect technology adoption in either direction. While we do not explore this, one potential explanation is that capital account restrictions are generally imposed over a time horizon that is shorter than that associated with decisions on the purchase of new capital goods.

Figure 16: Cumulative Response to Capital Account Restriction Episodes

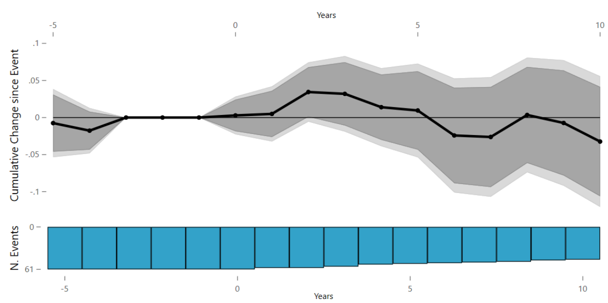
(a) Capital Account Openness Index



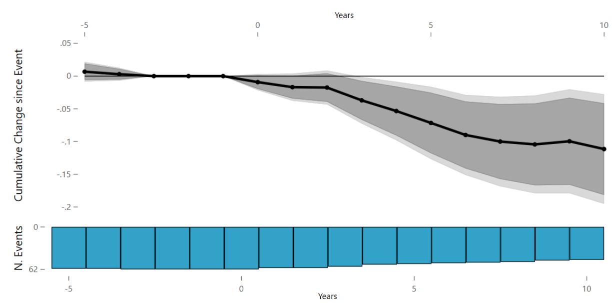
(b) Lifetime Portfolio Inflows



(c) Technology Adoption



(d) Output



Note: this figure displays the cumulative response of the Chinn-Ito indicator, the inverse hyperbolic sine of lifetime gross portfolio inflows, the natural logarithm of the Embodied Technology Imports (ETI) indicator, and the natural logarithm of real GDP per capita in PPP dollars to capital account restriction episodes. The events are defined as in Section 3, but for negative changes of KAOPEN. For each horizon h, the cumulative response corresponds to the coefficient β_h from equation (3). The results presented correspond to a specification with five stabilization lags, eight lags of the Chinn-Ito index, two lags of output growth, two lags of the outcome variable, two lags of trade openness defined as imports and exports of goods over GDP, two lags of the change in the asine transformation of net capital flows, and three lags of a dummy variable that indicates whether the country has an ongoing IMF program of any type. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using robust standard errors clustered at the country level. Bars display the number of events used to compute the response at each horizon.

6 Discussion

Our findings point to an important role of opening to external finance in upgrading countries' capital stocks. Conducting the analysis at the aggregate level seriously limits our understanding of the exact mechanisms by which such upgrading takes place. However, we believe that our findings on variables other than the ETI and the non-symmetric response of the ETI in the case of (partially-reversed) capital flow restrictions suggest that FDI flows play a crucial role in this process. Indeed, episodes of liberalizations see a significant increase in FDI that manifest right after the corresponding reforms, while these flows do not react in the case of restrictions.

How FDI promotes technology adoption is however not directly evident from findings at such a high level of aggregation. Three possibilities stand out. First, FDI inflows may raise GDP per capita, which in turn would lead to upgrading of capital goods as economies become more sophisticated. Stylized fact 2 suggests that this is a possibility since, in EMDEs, GDP per capita and ETI are positively correlated. If this were the case, we might expect that a decrease in GDP per capita would lead to a similar effect in the opposite direction, but we do not see any ETI response to capital restrictions. Second, FDI inflows may alleviate firms' credit constraints, allowing them to purchase better capital goods. Third, foreign investors might transmit their expertise and knowledge, leading to better capital purchases by local firms. These last two channels both appear plausible in light of our findings. The only way to disentangle these mechanisms would be to have firm-level data on technology adoption and capital flows by type, where pure credit flows and heterogeneity on the side of receiving firms might inform us on the peculiarity of FDI flows. A mildly negative response of other investment— which includes bank credit—in the case of capital flow restrictions might point to the fact that FDI provide more than just financing.

7 Conclusion

In this paper, we constructed a new index of technology adoption that covers 181 countries (of which 155 are EMDEs) over the period 1970-2020, which can be updated easily with access to UN COMTRADE and PATSTAT data. The ETI measures the sophistication of machinery imports based on a technology score for exporters. This technology score correlates strongly with alternative technology measures, notably the Economic Complexity Index. At the same time, the ETI correlates strongly with imports of intellectual property (for the subset of periods and countries that have this data). The ETI seems particularly useful to analyze technology in EMDEs, as we find a positive correlation of this index with GDP per capita only in EMDEs, where adoption of foreign technologies is the main path to upgrading the capital stock. In these countries, the ETI also predicts further growth.

We have shown that financial liberalization in EMDEs lead to significant increases in technology adoption, as measured by the ETI. The results are sizable, amounting to forty percent of a standard deviation increase over the 5 to 10 years following a positive change in the Chinn-Ito index. This technological upgrade is preceded by heightened capital inflows and followed by a level shift in PPP real GDP p.c., suggesting a long-lasting effect of opening up to financial flows. Our results are robust to controlling for the contemporaneous removal of trade barriers, more general short-run economic conditions, and to using alternative methods to estimate standard errors.

We envision two avenues for future research. First, our paper provided suggestive evidence of a chain of causality running from capital inflows to technology upgrading to higher output. This mechanism could be investigated further either empirically via mediation analysis or using firm-level data, or theoretically employing a structural model. Second, the ETI can be used in a variety of contexts and applications. In future work, we plan to study the ETI response to changes in countries' political alignment to assess the impact of geopolitical fragmentation on the adoption of technology.

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Appendix

A Data Appendix

A.1 KAOPEN Episodes Details

Table A1 contains the first ten observation of capital flow liberalization when sorting our dataset by ISO code and year. Moving left to right, the three columns after the country name report the change in KAOPEN observed for each year and country; the highest absolute change in KAOPEN in the five years preceding the episode (with a full stop if the Chinn-Ito index is missing for one of these years); and a dummy denoting whether the episode considered is "clean" according to our definition. Among these ten cases, only the observation for Argentina in 1993 is considered a clean episode, since no episode occurred in the five years before. The episodes for 1994-1997 are all considered "not clean" as they follow the 1993 liberalization. In a case like this one, our estimation strategy will consider the 1994-1997 increases as part of the liberalization episode starting in 1993, instead of new episodes. This contrasts with a traditional local projection approach, which would consider each case as a new shock in KAOPEN. The table also shows that we consider not clean cases where we do not have observations for the Chinn-Ito index in one of the previous five years. In the case of Angola, the KAOPEN series starts in 1993, so we cannot exclude that other changes in capital flow measures occurred in the five years preceding 1996. Appendix Table A2 reports all the "clean" events that we include in our sample.

Table A1: Examples of Capital Flow Liberalization Episodes

Year	ISO Code	Country Name	Δ KAOPEN	Max 5-year Change	Clean
1977	AFG	Afghanistan	0.82	1.33	0
1979	AFG	Afghanistan	0.69	1.33	0
1996	AGO	Angola	0.69	.	0
2010	ALB	Albania	1.07	1.07	0
1977	ARG	Argentina	1.77	0.25	0
1993	ARG	Argentina	2.53	0.00	1
1994	ARG	Argentina	0.25	2.53	0
1995	ARG	Argentina	0.25	2.53	0
1997	ARG	Argentina	1.07	2.53	0

Note: This table reports the first 10 observations with ΔKAOPEN > 0.245 together with the maximum absolute change in KAOPEN occurring in the five years before the episode considered. The last column contains a dummy denoting whether the episode is considered clean according to our definition.

Table A2: Clean Capital Flow Liberalization Episodes

ISO Code	Country Name	Episode Years
ARG	Argentina	1993
AUS	Australia	1984, 2012
AUT	Austria	1991
AZE	Azerbaijan	2002
BEL	Belgium	1990
BGD	Bangladesh	1992
BRA	Brazil	1998
BRB	Barbados	1993
BWA	Botswana	1987
CAF	Central African Republic	1991
CHL	Chile	1976, 1995
CHN	China	1993
CIV	Côte d'Ivoire	1993
CMR	Cameroon	1993
COD	Democratic Republic of the Congo	1997
COG	Congo, Republic of	1995
COL	Colombia	1990, 2004
CPV	Cabo Verde	2017
CRI	Costa Rica	2011
CYP	Cyprus	1993, 2003
DMA	Dominica	2005
DNK	Denmark	1988
DOM	Dominican Republic	1991
DZA	Algeria	1988
EGY	Egypt	1994
ESP	Spain	1993
FIN	Finland	1991

FRA	France	1990
GBR	United Kingdom	1979
GHA	Ghana	1994
GNQ	Equatorial Guinea	1984, 1995
GRC	Greece	1992
GRD	Grenada	1993, 2005
GTM	Guatemala	2001
HND	Honduras	2008
HRV	Croatia	2003
HTI	Haiti	1997, 2003
HUN	Hungary	1993
IRL	Ireland	1978, 1992
IRN	Iran	2001
ISL	Iceland	1992, 2016
ISR	Israel	1993
ITA	Italy	1982, 1990
JAM	Jamaica	1992
JOR	Jordan	1979, 1995
JPN	Japan	1979
KAZ	Kazakhstan	2019
KHM	Cambodia	2015
KOR	Korea	1978, 1988, 2008
LAO	Lao P.D.R.	1995
LKA	Sri Lanka	1977, 1992
LVA	Latvia	2003
MAR	Morocco	1986, 1993
MDG	Madagascar	1997
MDV	Maldives	1996
MLT	Malta	1994, 2004

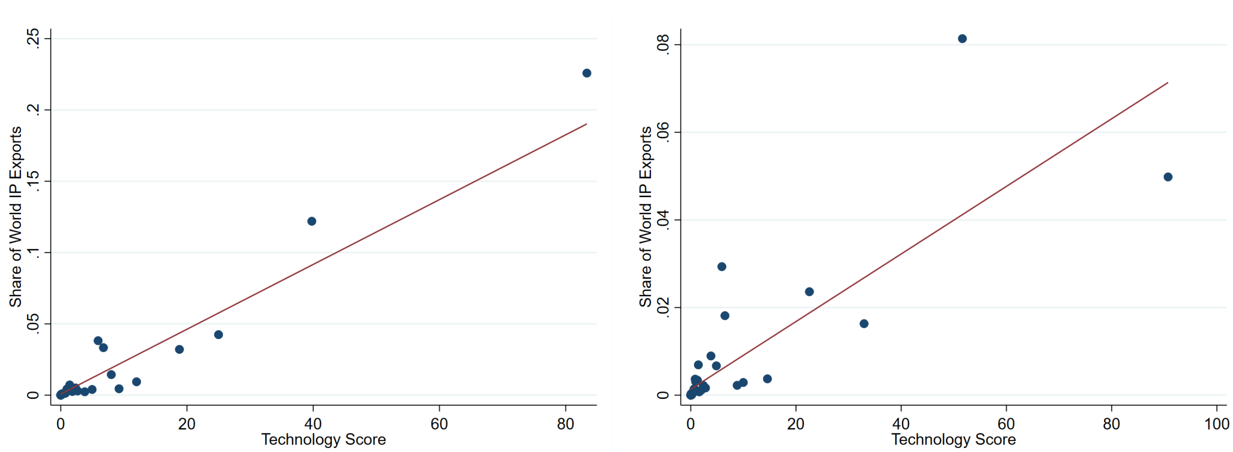
MMR	Myanmar	2020
MNG	Mongolia	2008
MUS	Mauritius	1984, 1993
MWI	Malawi	1995, 2013
MYS	Malaysia	2008
NER	Niger	1984, 1995
NGA	Nigeria	1986, 1997
NIC	Nicaragua	1990
NOR	Norway	1993
NPL	Nepal	1995
NZL	New Zealand	1976, 1984
OMN	Oman	2003
PHL	Philippines	1985, 1992
PNG	Papua New Guinea	2005
POL	Poland	1994, 2002, 2015
PRT	Portugal	1988
ROU	Romania	1992, 2002
RUS	Russia	2009
RWA	Rwanda	1994, 2010
SDN	Sudan	1987
SGP	Singapore	1978
SLE	Sierra Leone	2005, 2016
SLV	El Salvador	1992
SUR	Suriname	2016
SVK	Slovak Republic	2003
SWE	Sweden	1993
TCD	Chad	1993
THA	Thailand	2019
TJK	Tajikistan	2008

TTO	Trinidad and Tobago	1992
TUN	Tunisia	1992
TUR	Turkey	1989, 2008
UZB	Uzbekistan	2018
VNM	Vietnam	1993, 2008
WSM	Samoa	1993
ZAF	South Africa	1993
ZWE	Zimbabwe	1994, 2009

A.2 Omitted Descriptive Graphs

Figure 17: Binscatter of Exports of IP to the World versus Technology Rankings

(a) BPM 5, 1995-2012 (b) BPM 6, 2005-2021



Note: This figure plots share of world exports of intellectual property services (codes S266 and SH for the BPM5 and BPM6 versions, respectively) form the WTO-OECD BATIS data against technology scores for machinery, $S_{jg,t}$, computed as in Equation (2).

A.3 Balance between Treatment and Control

In this section, we discuss differences between treated country-year pairs and controls. As in other studies, this entails comparing units that receive treatment with those that do not. However, due to our methodology, we restrict attention to a specific set of observations to make this comparison relevant to our analysis, as well as to provide additional information relative to the event-study plots in the following section, which can be used to test for a clear violation of the parallel-trends hypothesis. In particular, here we compare countries that received a "clean" treatment in the period before the first KAOPEN change occurred to other countries that never saw an increase in this measure. Here we only exclude from the control group countries that see a year-on-year increase in KAOPEN larger than 0.254, allowing us a wider comparison in pre-trends than what is visible in the event-study graphs presented in the next section.[30]

Table A3 reports descriptive statistics for year-on-year changes of several variables in this sample of countries, restricting attention to non-advanced economies. This comparison is the most relevant to our difference-in-differences design, which requires parallel trends between treatment and control groups. Column (1) and (2) report averages for countries that do not see any increase in KAOPEN over the period and countries that receive a clean treatment, respectively. Column (3) reports the difference between clean treatment countries and never treated, after residualizing for year fixed-effects. We include time fixed-effects because events are clustered over time, which makes column (1) and (2) not fully comparable. We do not find any significant differences with the exception of the year-on-year changes in KAOPEN and the growth of GDP PPP per capita. It appears that, on average, countries that undergo capital flow liberalization experience larger restrictions in capital flow measures in the periods preceding treatment. By our definition of clean episodes, observations in column (2) cannot see any change in KAOPEN in the five years preceding liberalization, so the source of the difference between treatment and control is to be found more than five years before treatment. When we inspect event-study graphs, we only see that KAOPEN appears larger (and marginally significant) for treated units only for the estimates concerning 10 periods before the event for the full sample of countries, which is responsible for generating the significant difference in year-on-year KAOPEN changes in column (3). As shown in Figure 10, we do not see any significant difference in KAOPEN in any of the periods preceding treatment (plots with more than 10 lags are available on request). Given our assumption that treatment effects stabilize after five treatment periods, even significant distant differences in KAOPEN would not be enough to compromise the comparability between treatment and control units. On the other hand, GDP PPP per capita appears to be on a different trend in the two to three years before events take place (graph available on request). As a result, we choose to include two lags of GDP PPP per capita growth to match treatment and control units along this observable direction. Doing so ensures that we condition on this observable difference when carrying

[30]This does not correspond exactly to our regression specification, where we further restrict to controls that see *no change* in the KAOPEN measure. For example, we include observations for Nigeria before 1986 in the treatment group, and all available observations for Benin, since the latter only saw a *reduction* in the KAOPEN measure for the period covered by our sample. However, in our regression we would drop Benin from the control group for the five years after 1996, which registers a KAOPEN drop.

out our analysis. If this is indeed the only difference between treatment and control groups, the inclusion of GDP PPP per capita growth among controls ensure that we recover the correct causal effect of interest since the parallel trend assumption will hold *conditional on included covariates*.[31]

[31] The results on FDI/GDP are robust to restricting the sample to exclude the largest and smallest 1% observations.

Table A3: Balance between No KAOPEN Increase and Clean Treatment Observations, EMDEs

	(1)	(2)	(3)
Δ log(GDP)	0.031	0.036	0.002
	(0.064)	(0.058)	(0.003)
Δ log(GDP, PPP)	0.032	0.036	0.002
	(0.064)	(0.058)	(0.003)
Δ log(GDP, PPP, p.c.)	0.010	0.019	0.013***
	(0.065)	(0.056)	(0.003)
Δ log(ETI), baseline	0.010	0.005	-0.010
	(0.311)	(0.373)	(0.018)
Δ MATR	0.017	-0.019	-0.041
	(0.368)	(0.687)	(0.035)
Δ KAOPEN	-0.022	-0.047	-0.023**
	(0.129)	(0.229)	(0.011)
Δ FDI/GDP, pp	-0.038	0.060	-0.056
	(4.585)	(2.160)	(0.231)
Δ Net Capital Inflows, asinh	-0.434	0.064	0.074
	(17.686)	(17.475)	(1.232)
Δ Trade Openness	-0.005	-0.031	-0.042
	(0.250)	(0.863)	(0.036)
Δ Exports/GDP, goods, pp	-0.834	-1.007	-0.290
	(19.284)	(24.766)	(1.296)
Δ Imports/GDP, goods, pp	-0.089	-1.367	-1.769
	(12.935)	(33.743)	(1.453)
Δ No. IMF programs	0.128	0.166	0.025
	(0.352)	(0.387)	(0.024)
Observations	1,061	1,149	2,210

Note: This table reports the sample mean of selected variables for country-years that see no increase in KAOPEN over the sample period (column (1)) and for country-years of countries that receive a clean treatment for the years before the treatment occurs (column (2)). A clean treatment is defined as an increase in KAOPEN larger than 0.254, which occurs more than five years away from any previous changes in KAOPEN. Column (3) reports the difference in means after residualizing for year fixed effects, as obtained from a regression of the variable of interest on a dummy for the event of clean control. Standard deviations for means in columns (1) and (2) are reported in parentheses, while column (3) reports the standard error for the estimated dummy coefficient. "log(ETI), baseline" reports the logarithm of the ETI obtained from granted patents fractionalized by IPC4. "Net Capital Inflows, asinh" denotes the inverse hyperbolic sine transformation of lifetime cumulative gross capital inflows minus cumulative gross capital outflows. Stars denote significance: $^{*}\ p < 0.1,\ ^{**}\ p < 0.05,^{***}\ p < 0.01,$

B More Robustness

B.1 More on Technology Adoption

We dig deeper into the effect on technology adoption by repeating (3) using as outcome variable intellectual property (IP) imports and alternative variations of the ETI. Overall our main result is supported when considering these alternative outcomes. Figure 18 presents the results for imports of intellectual property, the ETI disaggregated by type of machinery (agriculture, manufacturing and mining, and other machinery), and two alternative assumptions on how we count patents (raw count and adjusting for family size). We find that lifetime IP imports increase by 20% five years after the event (Panel a). Due to data availability, the number of events decreases dramatically after five years, decreasing the precision of our estimates. However, we consider that this result is also evidence that technology adoption increases after liberalization events.

Panels (b) to (d) of Figure 18 present the decomposition by type of machinery. All types of machinery exhibit an increase after liberalization events, with results consistently significantly different from zero for manufacturing machinery over the analyzed horizon. Overall the improvement in technology takes place across the board.

Finally, on a more technical level on the construction of the ETI, panels (e) and (f) present the results using alternative assumptions to determine the stock of patents of a given country, aim at correcting for patent quality. Panel (e) further adjusts the baseline count by the patent family size, while Panel (f) adjusts the baseline count by forward citations. In both cases we find increases in the ETI that are statistically significant and in the same ballpark as our baseline estimates.

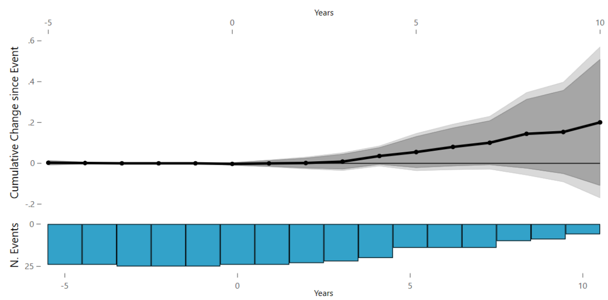
B.2 Alternative Econometric Assumptions

We explore two alternative specifications to account for known issues that could affect our main results. First, we employ Arellano & Bond's (1991) GMM procedure, as our estimates might suffer from Nickell's (1981) bias since we include lags of the dependent variables in several specifications. Second, we consider Driscoll & Kraay (1998) standard errors in order to account from cross-sectional correlation arising from the fact that reforms may occur at the same time in neighboring countries, and that generally shocks might be clustered at the regional level.

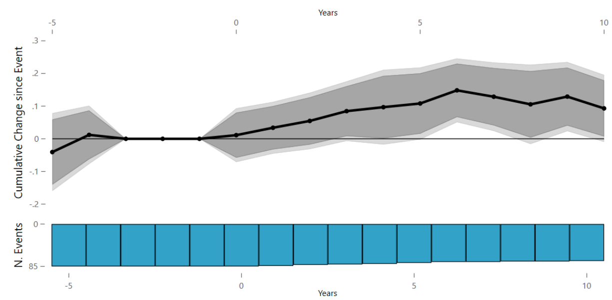
Figure 19 reports estimates pertaining to the Arellano-Bond procedure. To obtain these estimates, we employ the Stata command `xtabond2` (Roodman 2009), where we specify as potentially endogenous the lags of the dependent variable (in the `gmmstyle` option), and as exogenous (in the `ivstyle` option) year fixed effects, the event variable, and the GDP lags when GDP is not the main dependent variable. Depending on the horizon and

Figure 18: Cumulative Response to Liberalization, Other Technology Adoption Measures

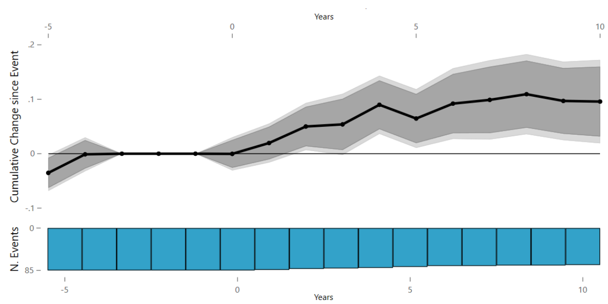
(a) Intellectual Property Imports, BPM5



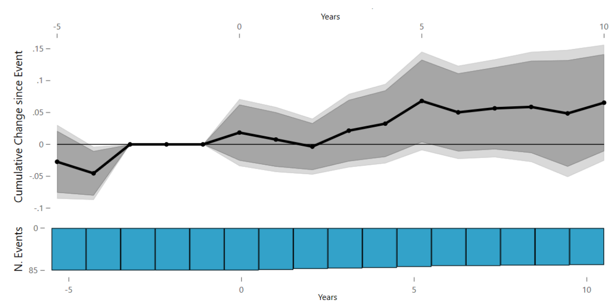
(b) Agriculture Machinery ETI



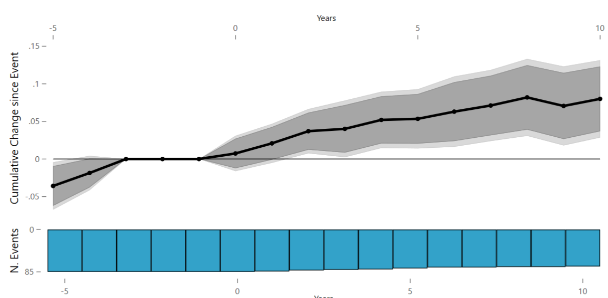
(c) Manufacturing and Mining ETI



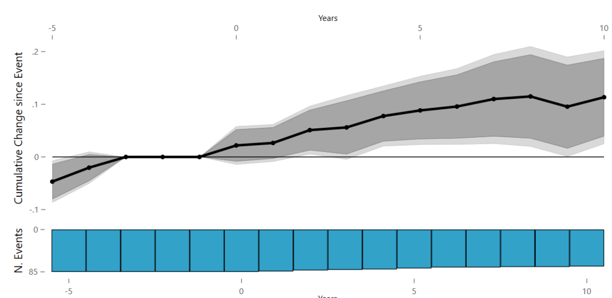
(d) Other Machinery ETI



(e) ETI Adjusted for Family Size



(f) ETI Adjusted by Forward Citations



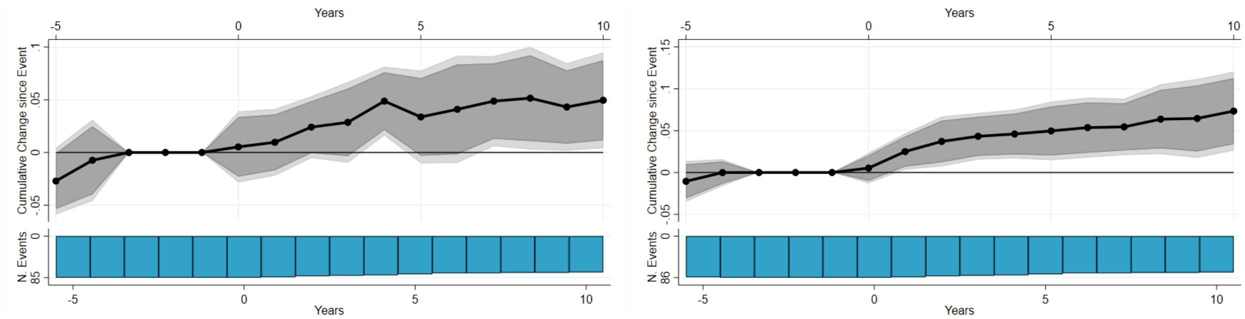
Note: this figure displays the cumulative response of the inverse hyperbolic sine of lifetime intellectual property imports (BPM5), and the natural logarithm of alternative definitions of the Embodied Technology Imports (ETI) indicator to capital account liberalization episodes as defined in Section 3. For each horizon h, the cumulative response corresponds to the coefficient β_h from equation (3). The results presented correspond to a specification with five stabilization lags, five lags of the Chinn-Ito index, two lags of log GDP, and two lags of the outcome variable. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using robust standard errors clustered at the country level. Bars display the number of events used to compute the response at each horizon.

the specification considered, we sometimes detect a failure of the Arellano-Bond AR(2) and AR(3) tests, for which reason we set the minimum number of lags for instruments at 4. We do not limit the maximum number of lags, but we utilize the `collapse` option to only generate one set of instruments for each variable and lag distance, rather than one for each time period, variable, and lag distance. This increases efficiency by decreasing the overall number of instruments included. This procedure requires a large number of lags of the variable under consideration, which is not always available for all countries in our unbalanced panel. As a result, we obtain different point estimates in addition to standard errors. In all cases, we obtain estimates that are within the 90% confidence bands of our baseline, with same qualitative features. In Nickell (1981), the approximate bias for large T is $-(1+\rho)/T$, so if this was a concern for our baseline specification, we would expect the estimates in Figure 19 to be larger than baseline. However, we mostly obtain smaller point estimates, indicating that the sample restriction to compute Arellano-Bond estimates more than compensates any potential bias arising for the inclusion of lags of the dependent variable among regressors. It is important to note that in these graphs, the number of events only represents the events included in the baseline, as it is not possible to recover this piece of information from estimates produced by `xtabond2`.

Figure 20 reports Driscoll & Kraay's (1998) confidence intervals around our baseline. We choose a bandwidth of 5 for the purpose of this estimation to mirror the number of stabilization lags. This seemed a sensible choice for the number of lags of autocorrelation to consider along the time dimension. In our experimentation, we found that large bandwidths produce more precise estimates, while smaller ones bring the estimated standard errors closer to the baseline. Consistent with this fact, the figure below shows that the Driscoll-Kraay procedure yields more precise estimates for most horizons relative to the baseline. All in all, our results appear robust to the alternative estimation procedures presented in this section.

Figure 19: Cumulative Response to Liberalizations, Arellano-Bond Estimation

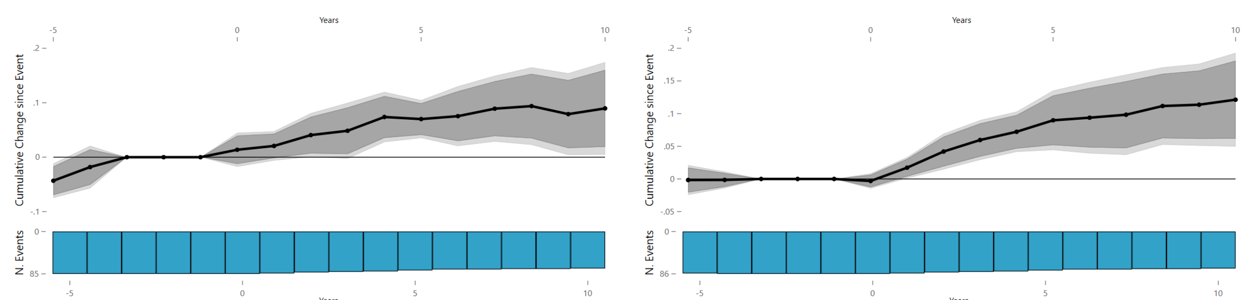
(a) Technology Adoption (b) Output



Note: this figure displays the cumulative response of the natural logarithm of the Embodied Technology Imports (ETI) indicator, and the natural logarithm of GDP to capital account liberalization episodes as defined in Section 3. For each horizon h, the cumulative response corresponds to the coefficient β_h from equation (3). The results presented correspond to a specification with five stabilization lags, two lags of log GDP, two lags of the outcome variable and no additional controls. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using the Arellano-Bond GMM estimation procedure.

Figure 20: Cumulative Response to Liberalizations, Driscoll-Kraay Standard Errors

(a) Technology Adoption (b) Output



Note: this figure displays the cumulative response of the inverse hyperbolic sine of lifetime total gross capital flows and gross foreign direct investment, the natural logarithm of the Embodied Technology Imports (ETI) indicator, and the natural logarithm of GDP to capital account liberalization episodes as defined in Section 3. For each horizon h, the cumulative response corresponds to the coefficient β_h from equation (3). The results presented correspond to a specification with five stabilization lags, two lags of log GDP, two lags of the outcome variable and no additional controls. The shaded areas correspond to the 90% (dark gray) and 95% (light gray) confidence intervals, using Driscoll-Kraay standard errors.

PUBLICATIONS

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