

FEDERAL RESERVE BANK OF ST. LOUIS

REVIEW

SECOND QUARTER 2023
VOLUME 105 | NUMBER 2

The Economic Impact of COVID-19 around the World

Fernando M. Martin, Juan M. Sánchez, and Olivia Wilkinson

Shipping Prices and Import Price Inflation

Maggie Isaacson and Hannah Rubinton

External Shocks versus Domestic Policies in Emerging Markets

Emilio Espino, Julian Kozlowski, Fernando M. Martin, and Juan M. Sánchez

**Tornado Cash and Blockchain Privacy:
A Primer for Economists and Policymakers**

Matthias Nadler and Fabian Schär

REVIEW

Volume 105 • Number 2



CENTRAL TO AMERICA'S ECONOMY®

President and CEO

James Bullard

Director of Research

Carlos Garriga

Deputy Director of Research

B. Ravikumar

Review Editors-in-Chief

Michael T. Owyang

Juan M. Sánchez

Special Policy Advisor

David C. Wheelock

Economists

Subhayu Bandyopadhyay

Alexander Bick

Serdar Birinci

Yu-Ting Chiang

YiLi Chien

Riccardo DiCecio

William Dupor

Maximiliano Dvorkin

Miguel Faria-e-Castro

Charles S. Gascon

Victoria Gregory

Nathan Jefferson

Kevin L. Kliesen

Julian Kozlowski

Fernando Leibold

Oksana Leukhina

Fernando M. Martin

Michael W. McCracken

Christopher J. Neely

Serdar Ozkan

Paulina Restrepo-Echavarría

Hannah Rubinton

Ana Maria Santacreu

Guillaume Vandenbroucke

Mark L. J. Wright

Christian M. Zimmermann

Publications Team

George E. Fortier

Jennifer M. Ives

Donna M. Stiller

74

The Economic Impact of COVID-19 around the World

Fernando M. Martin, Juan M. Sánchez, and Olivia Wilkinson

89

Shipping Prices and Import Price Inflation

Maggie Isaacson and Hannah Rubinton

108

External Shocks versus Domestic Policies in Emerging Markets

Emilio Espino, Julian Kozlowski, Fernando M. Martin, and Juan M. Sánchez

122

Tornado Cash and Blockchain Privacy: A Primer for Economists and Policymakers

Matthias Nadler and Fabian Schär

Review

Review is published four times per year by the Research Division of the Federal Reserve Bank of St. Louis. Full online access is available to all, free of charge.

Online Access to Current and Past Issues

The current issue and past issues dating back to 1967 may be accessed through our Research Division website: <http://research.stlouisfed.org/publications/review>. All nonproprietary and nonconfidential data and programs for the articles written by Federal Reserve Bank of St. Louis staff and published in *Review* also are available to our readers on this website.

Review articles published before 1967 may be accessed through our digital archive, FRASER: <http://fraser.stlouisfed.org/publication/?pid=820>.

Review is indexed in Fed in Print, the catalog of Federal Reserve publications (<http://www.fedinprint.org/>), and in IDEAS/RePEc, the free online bibliography hosted by the Research Division (<http://ideas.repec.org/>).

Subscriptions and Alerts

The *Review* is no longer printed or mailed to subscribers. Our last printed issue was the first quarter of 2020.

Our monthly email newsletter keeps you informed when new issues of *Review*, *Economic Synopses*, *Regional Economist*, and other publications become available; it also alerts you to new or enhanced data and information services provided by the St. Louis Fed. Subscribe to the newsletter here: <http://research.stlouisfed.org/newsletter-subscribe.html>.

Authorship and Disclaimer

The majority of research published in *Review* is authored by economists on staff at the Federal Reserve Bank of St. Louis. Visiting scholars and others affiliated with the St. Louis Fed or the Federal Reserve System occasionally provide content as well. *Review* does not accept unsolicited manuscripts for publication.

The views expressed in *Review* are those of the individual authors and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Board of Governors.

Copyright and Permissions

Articles may be reprinted, reproduced, republished, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. In these cases, there is no need to request written permission or approval. Please send a copy of any reprinted or republished materials to *Review*, Research Division of the Federal Reserve Bank of St. Louis, P.O. Box 442, St. Louis, MO 63166-0442; STLS.Research.Publications@stls.frb.org.

Please note that any abstracts, synopses, translations, or other derivative work based on content published in *Review* may be made only with prior written permission of the Federal Reserve Bank of St. Louis. Please contact the *Review* editor at the above address to request this permission.

Economic Data

General economic data can be obtained through FRED®, our free database with over 800,000 national, international, and regional data series, including data for our own Eighth Federal Reserve District. You may access FRED through our website: <https://fred.stlouisfed.org>.

The Economic Impact of COVID-19 around the World

Fernando M. Martin, Juan M. Sánchez, and Olivia Wilkinson

Abstract

This article provides an account of the worldwide economic impact of the COVID-19 shock. In 2020, it severely impacted output growth and employment, particularly in middle-income countries. Governments responded primarily by increasing expenditure, supported by an expansion of the supply of money and debt. These policies did not put upward pressure on prices until 2021. International trade was severely disrupted across all regions in 2020 but subsequently recovered. For 2021, we find that the adverse effects of the COVID-19 shock on output and prices were significant and persistent, especially in emerging and developing countries.

JEL codes: E52, E62, F34, F41, G15

Federal Reserve Bank of St. Louis *Review*, Second Quarter 2023, 105(2), pp. 74–88.
<https://doi.org/10.20955/r.105.74-88>

1. INTRODUCTION

For over two years, the world has been battling the health and economic consequences of the COVID-19 pandemic. As of the writing of this article, deaths attributed to COVID-19 have surpassed six-and-a-half million people.¹ Global economic growth was severely impacted: World output by the end of 2021 was more than 4 percentage points below its pre-pandemic trend.² International trade was also significantly disrupted at the onset of the pandemic. The pandemic also prompted a strong policy response, resulting in a rise of government deficits and debt as well as widespread increases in the money supply. Finally, after an initial decline, prices have soared, resulting in elevated inflation rates.

This article provides an account of the worldwide economic impact of the COVID-19 shock. This shock was not felt simultaneously around the world, and mitigation policies, both health related and economic, varied substantially across countries. Yet there are some significant similarities in outcomes, especially when considering the pandemic period as a whole. Our analysis focuses on the shock's effects on specific groups of countries, related by their level of development and geographical location.

We find that the COVID-19 shock severely impacted output growth and employment in 2020, particularly in middle-income countries. The government response, mainly consisting of increased expenditure, implied a rise in debt levels. Advanced countries, having easier access to credit markets, experienced the highest increase in indebtedness. All regions also relied on monetary policy to support the fiscal expansion, and hence the money supply increased everywhere. The specific circumstances surrounding the shock implied that the expansionary fiscal and monetary policies did not put upward pressure on prices until 2021. International trade was severely

1. See worldometer for more information.

2. In January 2020, the International Monetary Fund estimated world growth to be 3.3 percent for 2020 and 3.4 percent in 2021, making the combined estimated growth 6.8 percent. However, actual growth is estimated to be –3.5 percent in 2020 and 5.9 percent in 2021, making the combined actual growth 2.2 percent.

Fernando Martin is an assistant vice president and economist, Juan M. Sánchez is a vice president and economist, and Olivia Wilkinson is a senior research associate at the Federal Reserve Bank of St. Louis.

©2023, Federal Reserve Bank of St. Louis. The views expressed in this article are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Articles may be reprinted, reproduced, published, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. Abstracts, synopses, and other derivative works may be made only with prior written permission of the Federal Reserve Bank of St. Louis.

Table 1
Regional Attributes

Region	GDP per capita in 2019, USD	Total population in 2019, millions	Number of countries
Advanced	\$48,526	1,071	37
E&D Asia (excl. China and India)	\$3,809	873	16
China	\$10,243	1,434	1
India	\$2,099	1,366	1
E&D Europe	\$10,319	381	15
E&D Latin America & Caribbean	\$8,237	632	32
E&D Middle East & Central Asia	\$5,246	723	25
E&D Sub-Saharan Africa	\$1,702	1,013	42

SOURCE: Penn World Table, IMF, and authors' calculations.

NOTE: Total population here is less than the world total population for 2019 because this sample only includes countries that have nonmissing data for one or more of our variables of interest.

disrupted across all regions in 2020 but subsequently recovered. When extending the analysis to 2021, we find that the adverse effects of the shock on output and prices have been significant and persistent, especially in emerging and developing countries.

The rest of the article is organized as follows. Section 2 describes how we divide the world into regions and shows how excess mortality, output, and trade evolved during the pandemic. Section 3 explains our methodology and presents our results for the impact of the COVID-19 shock in 2020 on output, employment, government policy, inflation, and trade. Section 4 moves forward, to 2021, and discusses the overall impact on output and inflation. Section 5 concludes.

2. BASIC FACTS

We begin our analysis by showing evidence of the cross-country impact of the pandemic along three dimensions: excess mortality, output, and trade. Throughout the article, we divide the world into two main areas: advanced countries and emerging and developing countries. We use the International Monetary Fund's (IMF) classification to make this main partition and then further divide emerging and developing countries into regions.³ We consider advanced countries as a group, but we also look at individual countries in some of the charts in this section. In the case of emerging and developing (E&D) countries, we focus on specific regions: E&D Asia, E&D Europe, E&D Latin America and Caribbean, E&D Middle East and Central Asia, and E&D Sub-Saharan Africa. The E&D Asia region excludes China and India, which we report separately since they overwhelm any population-weighted averages.

Table 1 above provides information about average gross domestic product (GDP) per capita, total population, and the number of countries included for each of the areas and the regions we study.⁴ Advanced countries are far richer than other regions, with a GDP per capita of almost 50,000 dollars in 2019. Emerging and developing countries have much lower income: At the bottom, E&D Sub-Saharan Africa had a GDP per capita below 2,000 dollars in 2019, while at the top, E&D Europe had a GDP per capita just over 10,000 dollars in the same year. That is, income per capita in the richest emerging and developing region is only a fifth of that in advanced countries. Region populations range from 380 million in E&D Europe to about a billion in advanced countries and E&D Sub-Saharan Africa. The populations of China and India are the largest, about 1.4 billion each.

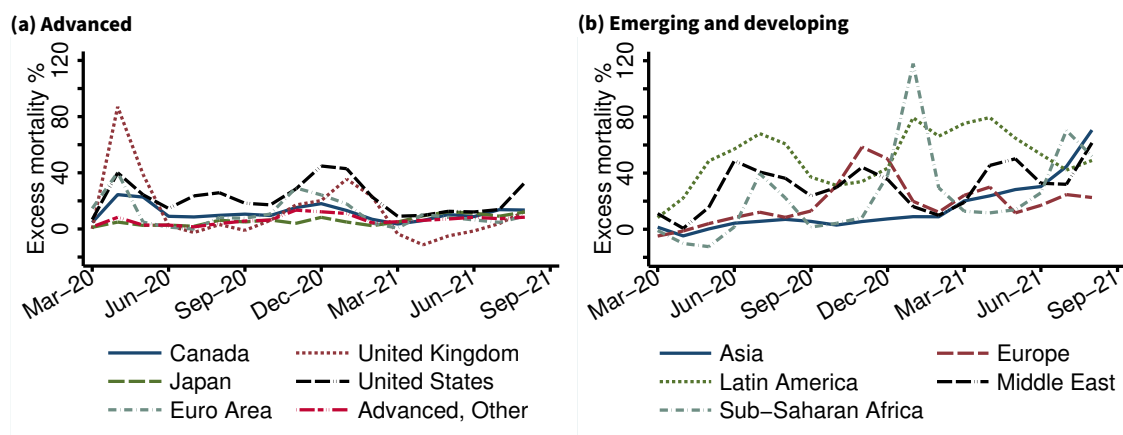
Figure 1 shows population-weighted averages of excess mortality across world regions. We define excess mortality as the difference between reported deaths and baseline deaths and present it as percentage of baseline deaths.⁵ Panel (a) on the left focuses on advanced economies, while panel (b) on the right includes emerging and developing regions. Although nearly all countries and regions experienced high excess mortality, emerging and developing countries fared much worse than advanced countries, especially during the first half of 2021.

3. The groupings can be found here.

4. The list of countries in each region and data sources are in Appendix 1.

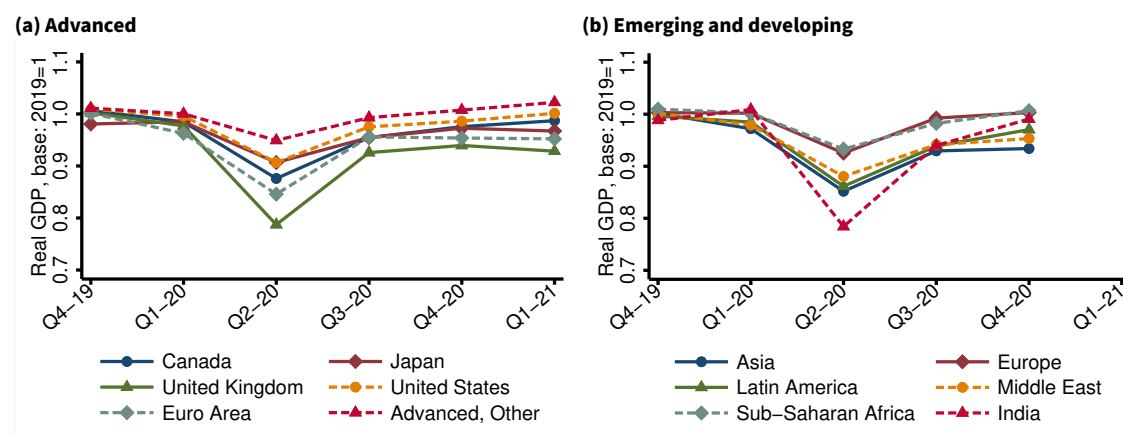
5. Excess mortality values (p -scores) are from Karlinsky and Kobak (2021) and Our World in Data (Ritchie et al., 2020). The baseline deaths for 2020–21 are estimated by fitting a linear regression model using mortality data from 2015 to 2019. See Karlinsky and Kobak (2021) for further details.

Figure 1
Excess Mortality



SOURCE: Karlinsky and Kobak (2021), Ritchie et al. (2020), IMF, and authors' calculations.
NOTE: Region averages are weighted by population. In panel (b), Asia represents E&D Asia (excluding China and India), Latin America represents E&D Latin America and Caribbean, Europe represents E&D Europe, and Middle East represents E&D Middle East and Central Asia. Data are shown at a monthly frequency. Countries with any missing observations within the time sample are excluded.

Figure 2
Real GDP



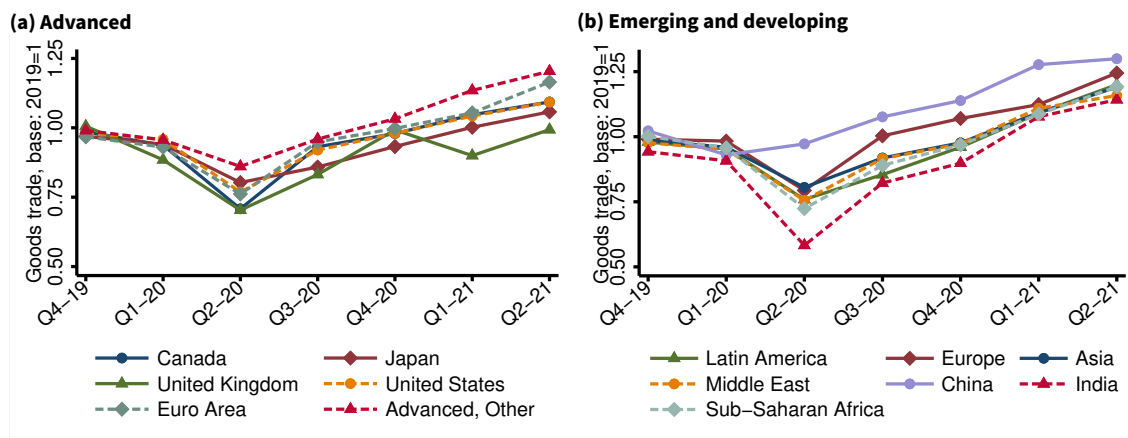
SOURCE: IMF and Organisation for Economic Co-operation and Development (OECD) via Haver Analytics and authors' calculations.
NOTE: In panel (b), Asia represents E&D Asia (excluding China and India), Latin America represents E&D Latin America and Caribbean, Europe represents E&D Europe, and Middle East represents E&D Middle East and Central Asia. Region averages are weighted by population, and GDP is seasonally adjusted.

In particular, E&D Latin America and Caribbean registered the highest mortality rates through much of the pandemic.

Figure 2 shows the evolution of real GDP by region. The series are normalized to 1 in 2019 to facilitate comparisons across time and regions. Panel (a) on the left shows that output in advanced countries declined significantly in the second quarter of 2020 when the pandemic first hit and lockdowns were the primary health mitigation policy tool. The plot shows that the United Kingdom suffered the most significant contraction, followed by the Euro area and Canada. Panel (b) on the right shows real GDP for emerging and developing countries. In this case, the most affected regions were E&D Latin America and Caribbean and E&D Asia (excluding China and India), followed by E&D Middle East and Central Asia. We also report output for India, which contracted severely in the second quarter of 2020. Interestingly, the range of the impact of the COVID shock on output is similar for advanced and developing countries.

Finally, there was a worldwide contraction in international trade at the onset of the pandemic. Figure 3 shows international trade per region, defined as the sum of the dollar amounts of goods exported and imported. We show trade in nominal terms, i.e., without removing the effect of price changes, and normalize it to one in

Figure 3
International Trade



SOURCE: OECD, International Financial Statistics (IFS), Haver Analytics, and authors' calculations.

NOTE: Total trade in goods is defined as the sum of goods exports and goods imports, in U.S. dollars. In panel (b), Asia represents E&D Asia (excluding China and India), Latin America represents E&D Latin America and Caribbean, Europe represents E&D Europe, and Middle East represents E&D Middle East and Central Asia. Region averages are weighted by population.

2019 to facilitate comparisons across time and regions. Emerging and developing countries, apart from China, shown in panel (b) on the right, experienced more significant declines in international trade on average than advanced countries, as shown in panel (a) on the left. However, trade recovered at a faster rate in emerging and developing countries; generally speaking, halfway through 2021, trade in these countries was about 20 percent above the pre-pandemic level.

3. COVID-19 IMPACT IN 2020

3.1 Methodology

To estimate the impact of the COVID-19 pandemic on economic outcomes and government policies, we primarily rely on the *World Economic Outlook* (WEO), published by the IMF.⁶ Specifically, we look at WEO reports for data on GDP per capita, net government borrowing as a percentage of GDP, government revenue as a percentage of GDP, government expenditure as a percentage of GDP, and inflation. We use other sources for additional variables. We obtain data for prices indexes and monetary aggregates from Haver Analytics, where available, or Refinitiv Eikon otherwise. The employment-to-population ratio is from the World Bank.

Within each region, we weight observations using the 2019 population from the Penn World Table 10.0. Each WEO report includes projections for the following five years as of publication. We use the projected 2020 values from the October 2019 report to estimate what outcomes would have been had the COVID-19 pandemic not occurred.⁷ We then compare these forecasts with the realized 2020 values published in the April 2022 report. Subtracting the estimated values from the realized values provides an estimate of the impact of COVID-19 for each variable. That is, we compute

$$Impact_{2020} = Realized_{2020} - Forecast_{2020}.$$

For variables not included in the WEO report, we compute the 2020 forecast using historical data, as described in Appendix 2.1.

3.2 Employment and Output

Table 2 shows that the impact of the pandemic on employment and output was significant in 2020. As mentioned above, we measure impact as the difference between the actual data and the pre-pandemic forecast. For advanced countries, the employment-to-population ratio was expected to grow by 0.45 percent but instead fell by 2.05 percent, a negative 2.50-percentage-point gap, which is our measure of the impact of the COVID-19 shock. The negative impact in emerging and developing regions was similar in magnitude except for E&D Latin America and Caribbean, where it amounted to 6.52 percentage points.

6. online here

7. See Appendix 3 for a robustness check of this assumption.

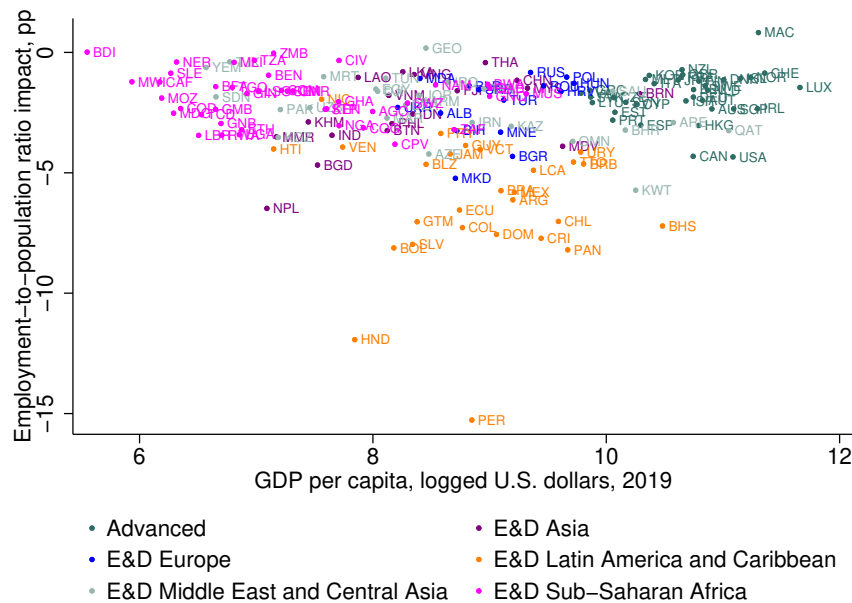
Table 2
2020 COVID-19 Impact on Indicators of Economic Activity by Region

	Change in employment-to-population ratio			Real GDP growth rate		
	2020 Forecast	2020 Data	COVID-19 impact	2020 WEO forecast	2020 Data	COVID-19 impact
Advanced	0.45	-2.05	-2.50	1.62	-4.83	-6.45
E&D Asia (ex. China and India)	0.20	-2.64	-2.84	5.74	-1.62	-7.36
China	-0.46	-1.62	-1.16	5.82	2.24	-3.57
India	-0.30	-3.74	-3.44	7.03	-6.60	-13.63
E&D Europe	0.11	-1.37	-1.48	2.57	-2.05	-4.62
E&D Latin America & Caribbean	0.12	-6.40	-6.52	1.56	-7.39	-8.96
E&D Middle East & Central Asia	-0.14	-2.30	-2.16	3.09	-2.12	-5.21
E&D Sub-Saharan Africa	0.02	-2.23	-2.25	4.52	-0.05	-4.57

SOURCE: World Bank, IMF, Penn World Tables, and authors' calculation.

NOTE: (i) Averages are weighted by population. (ii) If a country is missing either the forecasted value or actual 2020 value, that country is excluded from the sample. (iii) See Appendix 4.3 for further details on forecast errors. (iv) GDP is in constant prices.

Figure 4
COVID-19 Impact on Employment by Country



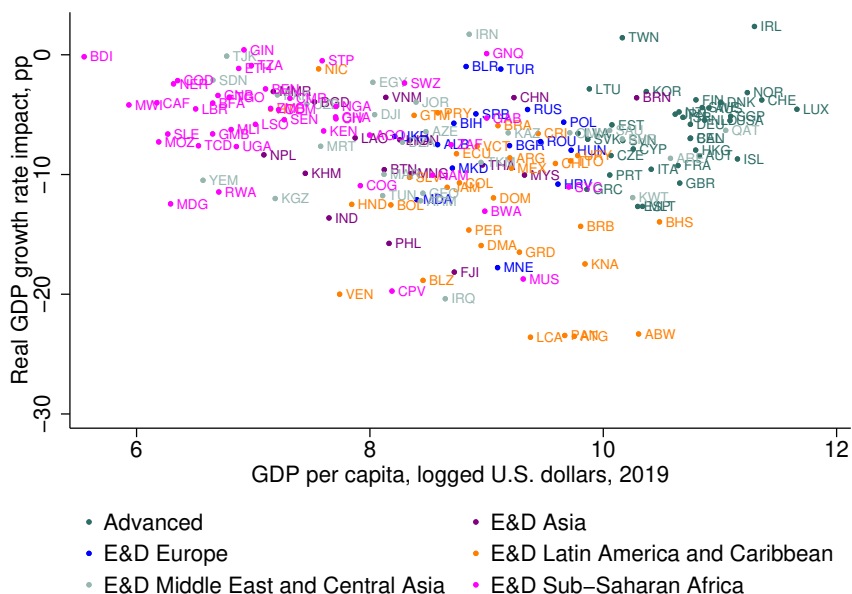
SOURCE: IMF, World Bank, Penn World Table, and authors' calculations.

Figure 4 plots the impact of COVID-19's impact on employment-to-population ratios against GDP per capita in 2019, country by country. The figure shows that E&D Latin America and Caribbean suffered a big impact, ranging from about -2 percentage points in Nicaragua to about -15 percentage points in Peru. The impact in other regions, both richer and poorer, was more compressed, clustering around 0 to -5 percentage points.

The right panel in Table 2 shows that GDP growth declined significantly due to the COVID-19 shock. The impact was approximately -6.45 percentage points for advanced countries. China and India are at the extremes, when compared to the averages for world regions, with an impact of -3.57 and -13.63, respectively. The impact in other emerging and developing regions ranged from -4.57 in E&D Sub-Saharan Africa to -8.96 in E&D Latin America and Caribbean.

Figure 5 presents a scatterplot showing the impact of COVID-19 on output growth against GDP per capita in 2019. This impact was between 0 and -10 percentage points for advanced countries and E&D Europe.

Figure 5
COVID-19 Impact on GDP by Country



SOURCE: IMF, Penn World Table, and authors' calculations.

Table 3
2020 COVID-19 Impact on Fiscal Policy by Region

	Revenue (% GDP)	Expenditure (% GDP)	Borrowing (% GDP)
Advanced	0.26	7.73	7.47
E&D Asia (excl. China and India)	-1.50	1.29	2.73
China	-3.45	0.92	4.63
India	-1.40	4.17	5.19
E&D Europe	0.31	3.72	3.74
E&D Latin America & Caribbean	-0.65	4.30	5.40
E&D Middle East & Central Asia	-2.37	-0.54	2.36
E&D Sub-Saharan Africa	-1.47	0.10	1.50

SOURCE: IMF, Penn World Table, and authors' calculations

NOTE: (i) Region averages are weighted by population. (ii) If a country is missing either the forecasted value or actual 2020 value, that country is excluded from the sample. (iii) See Appendix 4.3 for further details on forecast errors.

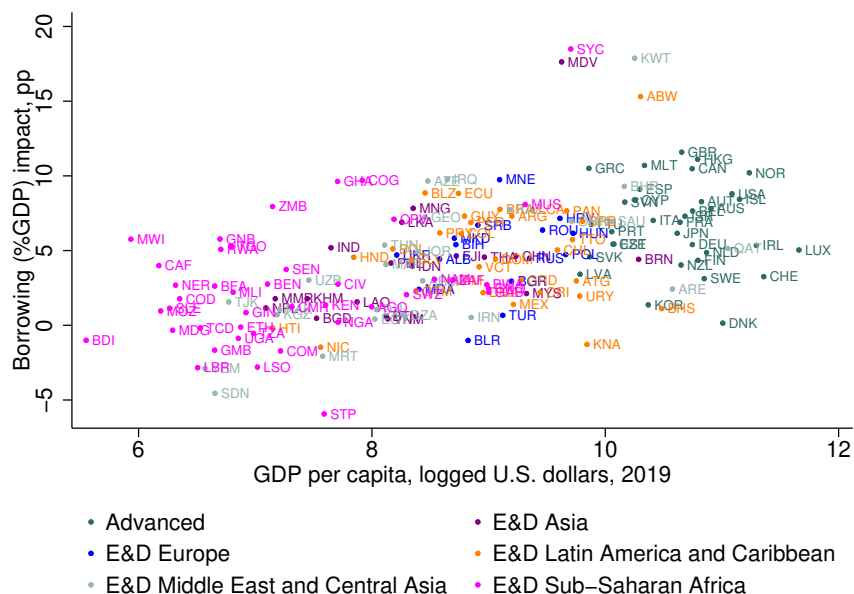
In other regions, the impact on output growth was more heterogeneous. It was worse for middle-income countries, with many suffering a contraction in GDP growth that was larger than 10 percentage points.

3.3 Revenue, Expenditure, and Net Borrowing

We now look at how the pandemic affected fiscal policy and focus on the impact on revenue, expenditure, and net borrowing, all expressed as fractions of GDP. Recall that we measure impact as the difference between the actual data and the pre-pandemic forecast. The first panel of Table 3 shows that, for most regions, the COVID-19 shock harmed revenue over GDP. This impact ranged from -3.45 percentage points in China to -0.65 percentage points in E&D Latin America and Caribbean. In contrast, for advanced countries, the impact on revenue over GDP was slightly positive, about 0.26 percentage points, while E&D Europe experienced an even higher positive impact, at 0.31 percentage points.⁸

8. See the tables in the online appendix for country-level details.

Figure 6
COVID-19 Impact on Borrowing by Country



SOURCE: IMF and authors' calculations.

As countries entered recessions induced by the lockdown policies designed to combat the pandemic, governments increased spending. The middle panel of Table 3 shows a positive impact of the COVID-19 shock on government expenditure over GDP for all regions except for E&D Middle East and Central Asia. Advanced countries experienced the most significant impact, at 7.73 percentage points. At the other end, E&D Sub-Saharan Africa experienced the smallest positive impact, at 0.10 percentage points, while E&D Middle East and Central Asia suffered a negative impact of -0.54 percentage points.

Naturally, increased expenditure and revenue shortfalls (or small increases, depending on the case) led to an increase in government debt. The right panel of Table 3 shows a positive impact of the COVID-19 shock on borrowing over GDP for all regions. Advanced countries had the most significant increase at 7.47 percentage points, which is explained by their significant increase in expenditure. E&D Sub-Saharan Africa and E&D Middle East and Central Asia had the smallest increases at 1.50 and 2.36 percentage points, respectively, which follows from their relatively small expenditure impacts. Figure 6 shows a positive correlation between real GDP per capita and the impact on borrowing as a percentage of GDP, implying that richer countries increased borrowing more than poorer countries. For the most part, this reflects the fact that richer countries have easier access to credit markets.

3.4 Monetary Aggregates and Inflation

In addition to the fiscal policy measures discussed in the prior section, many countries also used monetary policy to respond to the pandemic. The left panel of Table 4 shows the impact of the COVID-19 shock on the growth rate of the monetary base by region. The monetary base is typically defined as currency in circulation plus bank reserves. The shock's impact on the monetary base growth rate was positive across regions, ranging from 1.33 percentage points in India to 43.05 percentage points in advanced countries.

The middle panels of Table 4 show the shock's impact on the growth rate of M1 and M2 by region. The exact definitions of these monetary aggregates vary slightly by country. Since the message is similar regardless of the aggregate we choose, we focus on M2, which is the broader of the two. Typically, M2 includes currency in circulation, demand deposits, and items such as money market accounts and short-term time deposits. Basically, it is a combination of central and private banks' money-like liabilities. The COVID-19 shock positively impacted regions for the growth rate of M2, with E&D Latin America and Caribbean experiencing the most significant change at 11.87 percentage points and China experiencing the smallest change at 1.67 percentage points. Advanced countries are among those regions that increased M2 the most, with an impact of 11.39 percentage points.

Table 4
2020 COVID-19 Impact on Monetary Aggregates and Inflation by Region

	Monetary base growth rate	M1 growth rate	M2 growth rate	Inflation rate
Advanced	43.05	12.06	11.39	-1.17
E&D Asia (excl. China and India)	5.09	12.18	4.44	-1.33
China	1.57	5.69	1.67	-2.74
India	1.33	6.51	6.23	0.74
E&D Europe	18.82	19.91	7.19	0.69
E&D Latin America & Caribbean	12.07	24.62	11.87	-0.06
E&D Middle East & Central Asia	2.39	7.36	5.23	0.83
E&D Sub-Saharan Africa	10.81	9.39	10.79	2.99

SOURCE: IMF, Haver Analytics, Refinitiv Eikon, and authors' calculations.

NOTE: (i) Region averages are weighted by population. (ii) If a country is missing either the forecasted value or actual 2020 value, that country is excluded from the sample. (iii) See Appendix 4.3 for further details on forecast errors. (iv) The monetary base generally includes currency in circulation and bank reserves. (v) For the monetary base, we use the monetary base and population values for the Euro area within the advanced group. (vi) Inflation impact is truncated at -25% and 25%. Monetary aggregate impacts are truncated at the 5th and 95th percentiles. (vii) All values are end of period, and growth rates are annual.

Table 5
2020 COVID-19 Impact on International Trade by Region

	Real imports growth rate	Real exports growth rate
Advanced	-12.00	-13.95
E&D Asia (excl. China & India)	-16.31	-14.31
China	-3.47	-0.88
India	-21.45	-11.01
E&D Europe	-10.67	-9.42
E&D Latin America & Caribbean	-13.63	-13.55
E&D Middle East & Central Asia	-12.44	-12.80
E&D Sub-Saharan Africa	-11.41	-15.90

SOURCE: IMF, Penn World Tables, and authors' calculations.

NOTE: (i) Region averages are weighted by population. (ii) If a country is missing either the forecasted value or actual 2020 value, that country is excluded from the sample. (iii) See Appendix 4.3 for further details on forecast errors.

The last panel of Table 4 shows the shock's impact on annual inflation. Advanced countries, E&D Asia, China, and E&D Latin America and Caribbean experienced a negative impact on inflation, ranging from -2.74 to -0.06 percentage points. That is, in these regions, actual inflation in 2020 was lower than was forecasted pre-pandemic, in 2019. The remaining regions, E&D Europe, E&D Middle East and Central Asia, India, and E&D Sub-Saharan Africa, all experienced positive shocks to inflation ranging from 0.69 to 2.99 percentage points.

3.5 Trade

As discussed in the introduction, the COVID-19 shock hurt international trade in 2020. Table 5 shows the shock's impact on the growth rates of real imports and exports, computed as the difference between the actual realization and the forecast made before the pandemic. This impact was negative and significant on both import and export growth rates. That is, the growth rates of real imports and real exports were lower in 2020 than previously forecasted. The impact on real imports ranges from -21.45 percentage points in India to -3.47

Table 6
2020 COVID-19 Impact on Real GDP and Prices by Region

	Real GDP	Prices
Advanced	-3.27	1.30
E&D Asia (excl. China & India)	-10.73	-1.38
China	-1.40	-3.49
India	-12.23	3.04
E&D Europe	-1.07	6.09
E&D Latin America & Caribbean	-4.68	4.89
E&D Middle East & Central Asia	-4.59	1.91
E&D Sub-Saharan Africa	-4.47	6.46

SOURCE: World Bank, IMF, Penn World Tables, and authors' calculations.

NOTE: (i) Averages are weighted by population; see Appendix 4.1 for further details. (ii) If either the forecast or actual values are missing, then the country is excluded from the sample.

percentage points in China. The rest of the world regions had negative impacts ranging from -10.67 in E&D Europe to -16.31 in E&D Asia. The impact on real exports ranged from -15.90 percentage points in E&D Sub-Saharan Africa to -0.88 percentage points in China. The next least impacted region is E&D Europe, at -9.42. Advanced countries also suffered a significant adverse impact on international trade, -13.95, similar in magnitude to that of emerging and developing regions. The size of these effects reflects the economic disruptions caused by lockdowns during the initial phase of the pandemic.

4. THE RECOVERY OF 2021 AND THE OVERALL IMPACT OF COVID-19

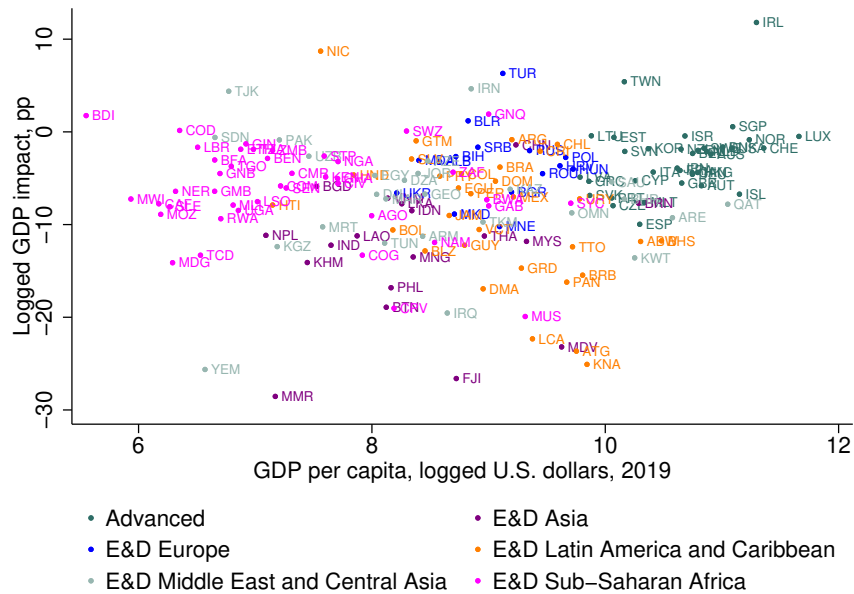
Economies around the world began to recover in 2021. Table 6 shows the accumulated impact of COVID-19 on output and prices over 2020 and 2021. For output, we take the difference between actual (log) real GDP for 2021 and the forecast made back in 2019. This calculation estimates where output is after two years of COVID-19, relative to the pre-pandemic trend. We perform the same calculation for the price level. One striking result is that all regions lag in terms of output, relative to their pre-pandemic trend. The impact is quite heterogeneous: E&D Europe is the region that was least affected, with real GDP only 1.07 percent below its pre-pandemic trend. India is the most affected, with real GDP 12.23 percent below its pre-pandemic trend. Notably, advanced countries are also lagging, with real GDP 3.27 percent below its pre-pandemic trend. Figure 7 plots the impact on real GDP against GDP per capita in 2019, country by country, to show the severity of the impact of the COVID-19 shock.⁹ Within all regions, there are several countries that suffered severely.

In most regions, end-of-period prices were higher than forecasted for 2021. A positive number in the last column of Table 6 indicates that the cumulative price inflation in 2020 and 2021 was higher than expected before the pandemic. The impact of the COVID-19 shock on inflation ranged from -3.49 percent in China to 6.46 percent in E&D Sub-Saharan Africa. In advanced countries, the overall impact of COVID-19 on inflation was also positive: By the end of 2021, prices were 1.30 percent higher than forecasted before the pandemic. Figure 8 plots the impact on inflation against GDP per capita in 2019, country by country.¹⁰ The impact is quite disparate, with both positive and negative cases, particularly as we move down the income distribution.

9. Countries with an impact below -30 percentage points (in this case, Macao) were cut off to make the chart more legible.

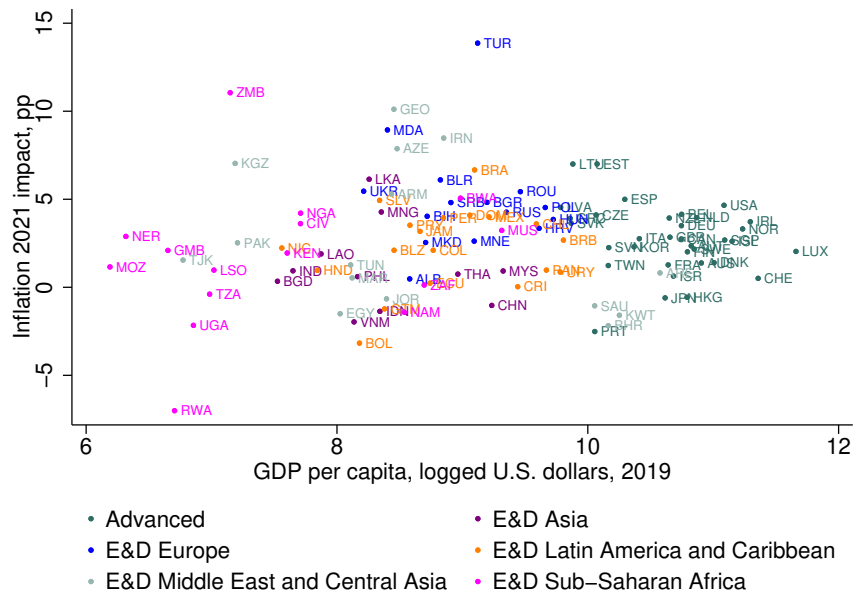
10. Countries with an impact above 15 percentage points (in this case, Argentina and Ethiopia) were cut off to make the chart more legible.

Figure 7
2020–21 COVID-19 Impact on Real GDP by Country



SOURCE: IMF and authors' calculations.

Figure 8
2020–21 COVID-19 Impact on Inflation by Country



SOURCE: IMF and authors' calculations.

5. CONCLUDING REMARKS

The economic consequences of the COVID-19 pandemic have been profound and persistent. In 2020, countries around the world experienced adverse impacts on real GDP growth, employment, and trade.¹¹ E&D Latin America and Caribbean, a region with many middle-income countries, suffered the most in terms of output

11. Country-level impact tables can be found in the online appendix.

growth and employment compared to other regions. India suffered the most overall in terms of output growth. The impact on government revenue was either negative or slightly positive but generally small. On the other hand, except for E&D Middle East and Central Asia, all regions experienced positive impacts on expenditure, in some cases quite substantial. As a result, borrowing increased everywhere as countries implemented their COVID-19 relief programs. Unsurprisingly, given their greater access to credit markets, advanced countries were able to increase expenditure and borrowing the most.

All regions experienced a positive impact on monetary aggregates as central banks around the world increased their supply of money. Combined with generous transfer programs, this resulted in an expansion of broader monetary aggregates, such as M1 and M2. The impact on inflation in 2020 was mixed, with some regions being affected positively and others negatively. By 2021, the impact of stimulus measures on prices started to materialize worldwide, with the notable exceptions of E&D Asia (excluding China and India) and China. Last, real output in 2021 was still below its pre-pandemic trend in all regions, with E&D Asia (excluding China and India) and India lagging significantly behind.

REFERENCES

- Ismail, Kareem, Roberto Perrelli, and Jessie Yang. 2020. Optimism bias in growth forecasts—the role of planned policy adjustments. *IMF* (November). <https://ssrn.com/abstract=3758062>.
- Karlinsky, Ariel, and Dmitry Kobak. 2021. Tracking excess mortality across countries during the covid-19 pandemic with the world mortality dataset. Edited by Miles P Davenport, Marc Lipsitch, Marc Lipsitch, Lone Simonsen, and Ayesha Mahmud. *eLife* 10 (June). issn: 2050-084X. <https://doi.org/10.7554/eLife.69336>. <https://doi.org/10.7554/eLife.69336>.
- Ritchie, Hannah, Edouard Mathieu, Lucas Rodeś-Guirao, Cameron Appel, Charlie Giattino, Estaban Ortiz-Ospina, Joe Hasell, Bobbie Macdonald, Diana Beltekian, and Max Roser. 2020. *Coronavirus pandemic (covid-19)*. Published online at OurWorldInData.org. <https://ourworldindata.org/coronavirus>.
- Timmermann, Allan. 2007. An evaluation of the world economic outlook forecasts. *IMF Econ Rev* 54:1–33. <https://doi.org/10.1057/palgrave.imfsp.9450007>.

APPENDIX 1. DATA SOURCES AND LIST OF COUNTRIES

Appendix 1.1 WEO data (October 2019 report and April 2022 report):

The WEO subject codes are in brackets. Access the databases on the World Economic Outlook page.

- GDP (percentage change) [NGDP_RPCH]: Annual percentages of constant price GDP are year-on-year (y-o-y) changes; the base year is country specific. Expenditure-based GDP is total final expenditures at purchasers' prices (including the free-on-board (f.o.b.) value of exports of goods and services) less the f.o.b. value of imports of goods and services. [SNA 1993]
- GDP (constant local currency) [NGDP_R]: We use this in 2020–21 GDP impact calculation, expressed in billions of national currency units. The base year is country specific. Expenditure-based GDP is total final expenditures at purchasers' prices (including the f.o.b. value of exports of goods and services) less the f.o.b. value of imports of goods and services. [SNA 1993]
- Revenue (%GDP) [GGR_NGDP]: Consists of taxes, social contributions, grants receivable, and other revenue. Revenue increases a government's net worth, which is the difference between its assets and liabilities (Government Finance Statistics Manual (GFSM) 2001, paragraph 4.20). Note: Transactions that merely change the composition of the balance sheet do not change the net worth position, for example, proceeds from sales of nonfinancial and financial assets or the incurrence of liabilities. Revenue is compiled on a fiscal year basis.
- Primary net lending/borrowing (%GDP) [GGXONLB_NGDP]: Is net lending (+)/borrowing (-) plus net interest payable/paid (interest expense minus interest revenue). Note that we multiply the value by -1, so positive values indicate borrowing.
- Total expenditure (%GDP) [GGX_NGDP]: Consists of total expense and the net acquisition of nonfinancial assets. Note: Apart from being on an accrual basis, total expenditure differs from the GFSM 1986 definition of total expenditure in the sense that it also takes the disposals of nonfinancial assets into account.
- Inflation [PCIEPCH]: Annual percentages of end-of-period consumer prices are y-o-y changes.
- Imports (y-o-y % change) [TM_RPCH]: Includes goods and services. Percentage change of volume of imports refers to the aggregate change in the quantities of total imports whose characteristics are unchanged. The basket of goods and services and their prices are held constant; therefore changes are due to changes in quantities only. [Export and Import Price Index Manual: Theory and Practice, Glossary]
- Exports (y-o-y % change) [TX_RPCH]: Includes goods and services. Percentage change of volume of exports refers to the aggregate change in the quantities of total exports whose characteristics are unchanged. The basket of goods and services and their prices are held constant; therefore changes are due to changes in quantities only. [Export and Import Price Index Manual: Theory and Practice, Glossary]

Appendix 1.2 Other data:

- Monetary aggregates: Values of monetary base, M1 and M2, are from each country's central bank and are downloaded via Haver Analytics (EMERGE, CANADA, and IFS databases), Refinitiv Eikon, or the central bank's website depending on availability. The values are in local currency and are not seasonally adjusted. For most countries, observations are end-of-period values at a monthly frequency. We use the December values for each year. When this is not the case, the quarterly data reflect the end-of-quarter values, and we use the fourth quarter values for each year.
- Employment: The employment-to-population ratio used in the tables is from the World Bank and is available at a yearly frequency. The observations are the percentage of employment to population for persons 15 years and older (modeled International Labour Organization (ILO) estimate). Access [here](#).
- GDP time series: Quarterly data are seasonally adjusted, in real local currency from Haver Analytics. Specifically, we use the IFS, EMERGE (data for emerging and developing countries), and OECD databases. We prioritize OECD data followed by IFS data and then fill any remaining gaps with EMERGE data. The values are normalized, where the average GDP for 2019 is equal to one.
- Trade time series: We obtain quarterly, seasonally adjusted import and export values (of goods) in total U.S. dollar amounts traded from Haver Analytics and OECD. Specifically, we use the EMERGE (data for emerging and developing countries) database from Haver Analytics. Total trade is the summation of the two values by country and quarter. The values are normalized, where average trade for 2019 is equal to one. The OECD series are from the BOP6 category on stats, available on the OECD webpage.

Table Appendix 1.1
Countries Included by Region

Advanced	E&D Asia	E&D Europe	E&D Latin America & Caribbean	E&D Middle East & Central Asia	E&D Sub-Saharan Africa
Australia	Bangladesh	Albania	Aruba	U.A.E.	Angola
Austria	Brunei	Bulgaria	Argentina	Armenia	Burundi
Belgium	Bhutan	Bosnia/Herzegovina	Antigua & Barbuda	Azerbaijan	Benin
Canada	Fiji	Belarus	The Bahamas	Bahrain	Burkina Faso
Switzerland	Indonesia	Croatia	Belize	Djibouti	Botswana
Cyprus	Cambodia	Hungary	Bolivia	Algeria	Central African Republic
Czech Rep	Lao PDR	Moldova	Brazil	Egypt	Cote d'Ivoire
Germany	Sri Lanka	North Macedonia	Barbados	Georgia	Cameroon
Denmark	Maldives	Montenegro	Chile	Iran	Congo, Dem Rep
Spain	Myanmar	Poland	Colombia	Iraq	Republic of Congo
Estonia	Mongolia	Romania	Costa Rica	Jordan	Comoros
Finland	Malaysia	Russia	Dominica	Kazakhstan	Cabo Verde
France	Nepal	Serbia	Dominican Rep	Kyrgyz Republic	Ethiopia
United Kingdom	Philippines	Turkey	Ecuador	Kuwait	Gabon
Greece	Thailand	Ukraine	Grenada	Morocco	Ghana
Hong Kong SAR	Vietnam		Guatemala	Mauritania	Guinea
Ireland			Guyana	Oman	Gambia
Iceland			Honduras	Pakistan	Guinea-Bissau
Israel			Haiti	Qatar	Eq Guinea
Italy			Jamaica	Saudi Arabia	Kenya
Japan			St Kitts & Nevis	Tajikistan	Liberia
Korea			St Lucia	Turkmenistan	Lesotho
Lithuania			Mexico	Tunisia	Madagascar
Luxembourg			Nicaragua	Uzbekistan	Mali
Latvia			Panama	Yemen, Rep of	Mozambique
Macao			Peru		Mauritius
Malta			Paraguay		Malawi
Netherlands			El Salvador		Namibia
Norway			Trin/Tobago		Niger
New Zealand			Uruguay		Nigeria
Portugal			St Vincent/Grens		Rwanda
Singapore			Venezuela		Senegal
Slovak Republic					Sierra Leone
Slovenia					Sao Tome & Principe
Sweden					eSwatini
Taiwan					Seychelles
United States					Chad
					Togo
					Tanzania
					Uganda
					South Africa
					Zambia

NOTE: Some countries are missing data for one or more variables of interest.

APPENDIX 2. NOTES ON TABLE CALCULATIONS:

In the tables, we drop Lebanon, Sudan, Syria, Suriname, and Zimbabwe from the sample because these countries were facing economic turmoil/high inflationary pressures before/regardless of COVID-19. Because the tables are population weighted, India's and China's large populations skew the numbers for E&D Asia, so they are included separately in the tables.

- **Calculating the 2020–21 GDP impact:** We take the forecasted GDP growth rates for 2020 and 2021 from the October 2019 WEO report. We apply those growth rates to annual 2019 GDP data to get the estimated 2021 GDP. The 2020–21 COVID-19 impact is 100 times the difference between the logged 2021 estimated GDP and logged actual 2021 GDP.
- **Calculating the 2020–21 inflation impact:** We take the forecasted end-of-period inflation rates for 2020

and 2021 from the October 2019 WEO report. We apply those growth rates to end-of-period 2019 Consumer Price Index (CPI) values to get the estimated 2021 end-of-period CPI. The 2020–21 COVID-19 impact is 100 times the difference between the logged 2021 estimated end-of-period CPI and the logged actual end-of-period 2021 CPI.

Appendix 2.1 Calculating Impact for the Variables Not in the WEO Report

- **Employment-to-population ratio change impact:** We take the employment-to-population ratio (%) for each year from the World Bank. The average percentage point change in the employment-to-population ratio from 2016 to 2019 is taken as the 2019 ratio minus the 2016 ratio, divided by three. This number is taken as a forecast for the expected change in the employment to population for 2020. The actual percentage point change in employment for 2020 is the ratio of employment to population for 2020 less the ratio of employment to population for 2019. The impact is the percentage point difference between the actual change in the employment-to-population ratio and the forecasted change in the employment-to-population ratio.
- **Monetary aggregate growth rate impact:** To obtain the forecasted value for 2020, we calculate the annualized growth rate for the monetary aggregate from 2017 to 2019 (i.e., the 2017–18 growth rate and the 2018–19 growth rate, annualized). The actual growth rate is the growth rate from 2019 to 2020 of the monetary aggregate. Then the impact is the percentage point difference between the forecasted growth rate for 2020 and the actual growth rate for 2020.

APPENDIX 3. FORECAST ERRORS BEFORE THE COVID-19 PANDEMIC

Our methodology relies on the forecast made in 2019 for several macroeconomic variables for the years 2020 and 2021. One concern may be the accuracy of these forecasts. For most variables, we use the 2019 WEO forecasts. For those not included there, we made our forecast based on data available in 2019 as described in Appendix 2.1.

When can this be a problem? For example, if the WEO has consistently optimistic forecasts, then our impact measure will be too negative because even without COVID-19, the year 2020 was going to be worse than expected. This is an important concern because there is previous evidence of optimism bias in the WEO reports (Ismail, Perrelli, and Yang, 2020; Timmermann, 2007).

In this section, we analyze forecast errors for the years 2011–19 to provide support for our methodology. The top panel of Table Appendix 3.1 contains percentile values of historical forecast errors in the WEO report by region (advanced and emerging and developing). The forecast error is the difference between the value for the variable in year n from the April 2022 WEO report and the forecast value for year n from the October WEO report in year $n - 1$.¹² The impact for 2020, presented in the last column, is colored in green when it is outside the 10th–90th percentile range, black when it is outside the 25th–75th percentile range, and red when it is inside the 25th–75th percentile range.

First note that the 2020 impact estimate for change in GDP and borrowing (% GDP) are outside of the 10th–90th percentile range, for both the advanced and emerging groups. This indicates that the impact values are significant for 2020. Likewise, the impact values for expenditure (%GDP), imports volume, and exports volume are also very large and somewhat significant. The impact estimates for inflation and revenue (%GDP) are not significant.

To forecast the variables not included in the WEO reports, we estimated the forecasts for M1, M2, the monetary base, and the employment-to-population ratio for the period 2011 to 2019 using a similar methodology as in Appendix 2.1. We then take the forecast error to be the difference between the variable in each year and the forecast for that year. The bottom panel of Table Appendix 3.1 contains percentile values of these forecast errors. The 2020 impacts for employment-to-population ratio and the change in M1 are significant in both regions since the values are outside the historical forecast error 10th–90th percentile range. Similarly, the impact values for change in M2 and the change in monetary base are significant for the advanced group. The impact value for change in M2 is somewhat significant for the emerging group, and the impact value for the monetary base in the emerging group is not significant since it is inside the 25th–75th percentile range.

12. For example, the variable forecasts for 2015 are taken from the October 2014 WEO report and the actual values for 2015 are taken from the April 2022 report.

Table Appendix 3.1
Forecast Errors for 2011–2019 and 2020 Impact

Group	Variable	Error percentiles 2011-2019					Impact
		p10	p25	p50	p75	p90	2020
Advanced	Change GDP	-1.54	-0.79	-0.01	0.81	1.92	-6.45
Emerging	Change GDP	-3.81	-1.75	-0.3	0.77	2.11	-7.16
Advanced	Borrowing (%GDP)	-2.21	-1.28	-0.28	0.67	1.71	7.47
Emerging	Borrowing (%GDP)	-3.25	-1.41	-0.08	1.39	3.39	3.76
Advanced	Expenditure (%GDP)	-3.89	-2.03	-0.35	1.1	3.22	7.73
Emerging	Expenditure (%GDP)	-8.52	-4.87	-1.7	0.54	3.33	1.86
Advanced	Imports volume (% YoY)	-5.09	-2.77	-0.45	2.28	5.2	-12.00
Emerging	Imports volume (% YoY)	-14	-6.94	-0.7	4.58	11.2	-12.72
Advanced	Exports volume (% YoY)	-4.24	-2.49	-0.23	2.05	4.99	-13.95
Emerging	Exports volume (% YoY)	-14.93	-7.38	-1.8	2.92	8.45	-10.29
Advanced	Inflation	-1.87	-1.15	-0.43	0.33	1.14	-1.17
Emerging	Inflation	-3.54	-2.05	-0.65	0.93	3.03	-0.03
Advanced	Revenue (%GDP)	-2.93	-1.28	0.07	1.24	3.2	0.26
Emerging	Revenue (%GDP)	-8.45	-4.48	-1.43	0.58	2.87	-1.82
Advanced	Change emp to pop	-0.49	-0.1	0.34	0.75	1.22	-2.50
Emerging	Change emp to pop	-0.76	-0.26	0.02	0.37	1	-2.70
Advanced	Change M1	-7.32	-4.03	-0.8	3.08	5.94	12.06
Emerging	Change M1	-10.96	-5.77	-0.6	3.67	9.17	9.79
Advanced	Change M2	-3.81	-1.82	-0.05	1.61	4.35	11.39
Emerging	Change M2	-7.83	-3.86	-0.52	2.65	6.11	5.86
Advanced	Change monetary base	-14.17	-4.56	-0.2	5.87	17.38	43.05
Emerging	Change monetary base	-16.94	-7.9	-0.87	6.67	14.25	5.39

SOURCE: WEO, Haver Analytics, Penn World Table, World Bank, Refinitiv Eikon, and authors' calculations.

NOTE: The impact for 2020 is colored in green when it is outside the 10th–90th percentile range, black when it is outside the 25th–75th percentile range, and red when it is inside the 25th–75th percentile range.

Shipping Prices and Import Price Inflation

Maggie Isaacson and Hannah Rubinton

Abstract

During the pandemic, there have been unprecedented increases in the cost of shipping goods accompanied by delays and backlogs at the ports. At the same time, import price inflation has reached levels unseen since the early 1980s. This has led many to speculate that the two trends are linked. In this article, we use new data on the price of shipping goods between countries to analyze the extent to which increases in the price of shipping can account for the rise in U.S. import price inflation. We find that the pass-through of shipping costs is small. Nevertheless, because the rise in shipping prices has been so extreme, it can account for between 3.60 and 5.87 percentage points per year of the increase in import price inflation during the post-pandemic period.

JEL codes: F14, R41, E31

Federal Reserve Bank of St. Louis *Review*, Second Quarter 2023, 105(2), pp. 89-107.
<https://doi.org/10.20955/r.105.89-107>

1. INTRODUCTION

After the first months of the pandemic passed and the economy began to reopen, two things became central to the national discussion—supply chain disruptions and price increases. The supply chain disruptions took many forms, from delays and backlogs at ports (Smialek and Nelson, 2021) to low inventory in key sectors (Leibovici and Dunn (2021)). The 2022 *Economic Report of the President* featured a chapter on supply chains, stating that “[t]hese highly publicized disruptions and product shortages made the public painfully aware of the many steps involved in getting a product produced, transported, and placed on shelves or doorsteps” (*Economic report of the president, april, 2022*). Supply chain issues can be seen in the stark increase in the price of shipping goods by sea between countries (Figure 1), which increased almost sevenfold during the pandemic. Meanwhile, the U.S. has experienced some of the highest annual rates of inflation since the 1980s¹

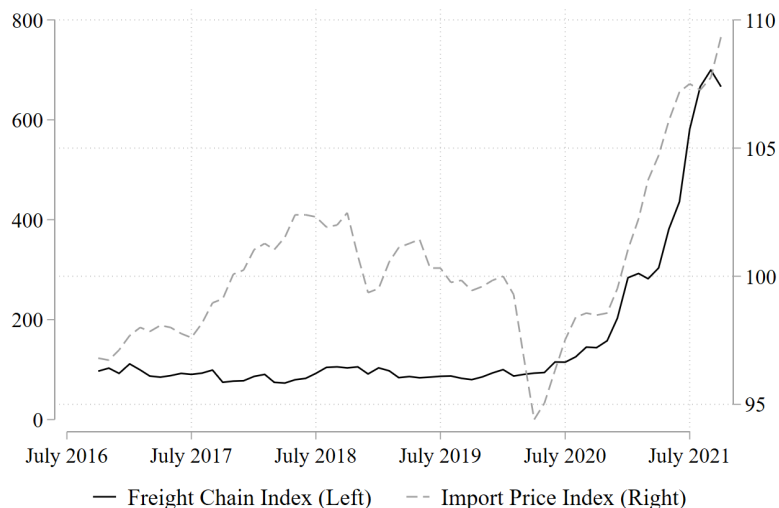
Figure 1 shows the sharp increase in import prices, as measured by an import price chain index from the Bureau of Labor Statistics (BLS), and the sharp increase in shipping costs, measured with the Freightos-Baltic

1. The information on annual rates of inflation comes from the Bureau of Labor Statistics and pulled from FRED at <https://fred.stlouisfed.org/series/CPILFESL>.

Hannah Rubinton is an economist and Maggie Isaacson is a senior research associate at the Federal Reserve Bank of St. Louis.

©2023, Federal Reserve Bank of St. Louis. The views expressed in this article are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Articles may be reprinted, reproduced, published, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. Abstracts, synopses, and other derivative works may be made only with prior written permission of the Federal Reserve Bank of St. Louis.

Figure 1
Freight Price Index and Import Price Index



NOTE: The figure above displays two chain indexes with January of 2020 as the base month. The solid line, graphed on the left axis, displays the price of freight shipping, and the dotted line, graphed on the right axis, displays import prices over time.

Freight Chain Index². The simultaneous increase in the price of shipping goods and import prices has led to speculation that the two issues are linked. Pete Buttigieg, secretary of transportation, noted in late 2021 that “[t]here’s no question that when you have a scarcity of access to shipping, you’re going to see upward pressure on prices, and that’s going to be part of our challenge when it comes to inflation” (Swanson, 2022).

In this article, we examine the relationship between shipping costs and prices. The main exercise is an examination of the pass-through of shipping costs to import price inflation using variation across products in exposure to shipping price increases. Our analysis proceeds in two steps. We first create a commodity-level measure of exposure to the increase in shipping prices. To do so, we leverage a new dataset on the cost of shipping goods by sea between the U.S. and its trade partners. We merge the shipping prices with data from the United Nations Commodity Trade Statistics Database (Comtrade), which gives the share of a commodity imported from each partner country. Then, for each commodity, we average shipping price growth across trade partners, weighted by the import share of each trade partner. As a second step, we merge our commodity-level measure of shipping prices with commodity-level import price data from the BLS. Finally, we use our dataset to examine the relationship between import price inflation and our measure of exposure to the increase in shipping prices.

In general, we find a modest amount of pass-through from shipping price growth to import price inflation. After the pandemic, we estimate that a 1-percentage-point increase in shipping price growth leads to an increase in import price inflation of 0.0684 percentage points. While this is a fairly modest number, the increase in shipping prices has been so extreme during the pandemic that the implications for import price inflation are large. On average, shipping price growth increased by 86 percent during the pandemic, which implies an increase in import price inflation of 5.87 percentage points per year.

We then look at the heterogeneity of this pass-through over time and across commodity types. We find a more significant pass-through after 2020 and for product types that ship a higher share of goods by sea than other types of transportation as well as for products with a higher ratio of the cost of shipping by sea to the cost of the good. We also find more pass-through in food and materials goods as opposed to consumer goods and

2. The Freightos-Baltic Chain Index was pulled from <https://fbx.freightos.com/> in early 2022.

in machines, electronics, and parts. This pattern seems to suggest that whether the type of good is perishable and whether it is an intermediate good versus final good might matter for the pass-through.

Finally, we use our estimates of the pass-through from shipping costs to import prices to create an upper and lower bound on the impact on inflation. We find that the rise in shipping costs during the pandemic can account for between 68 and 111 percent of the increase in import price inflation and 15 and 25 percent of the increase in the producer price index (PPI). The lower impact on PPI is because of the modest impact that import prices have on domestic inflation, as found by Amiti, Heise, Wang, et al. (2021) and Amiti, Redding, and Weinstein (2019). We conclude that while the disruptions in the shipping industry played a large role in import price inflation, other factors such as demand shocks (Guerrieri et al. (2021)), fiscal stimulus (Soyres, Santacreu, and Young (2022)), and other supply shocks (Leibovici and Dunn (2021) and LaBelle and Santacreu (2022)) are necessary to generate the extreme rise in domestic prices.

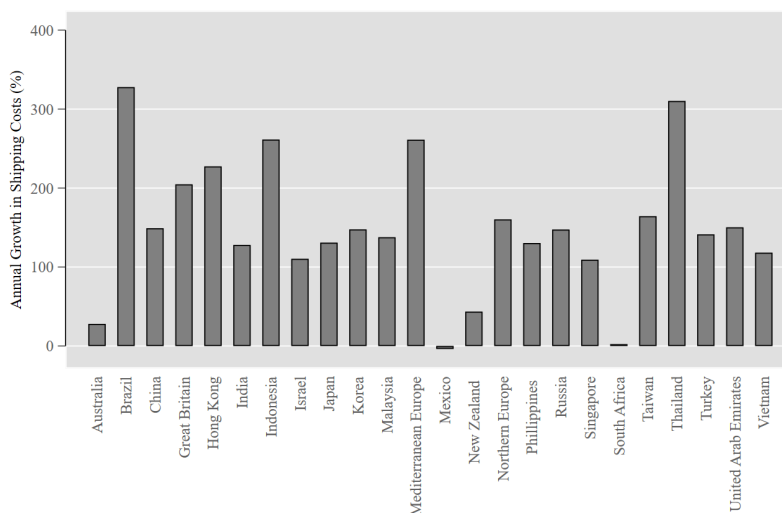
The literature on the relationship between supply chain disruptions and inflation is small but growing. The theoretical literature shows that trade fluctuations and supply chain disruptions will impact U.S. inflation with important implications for monetary policy. Leibovici and Santacreu (2015) develop a small open economy model with trade and find that policymakers should take trade fluctuations into account when developing monetary policy. Wei and Xie, 2020 find that as supply chain complexity increases over time, monetary policy targeting PPI inflation yields lower welfare losses than monetary policy targeting CPI inflation. Finally, Comin and Johnson (2021), using a New Keynesian model with a small open economy, find that firm-level constraints (e.g., temporary capacity limits for foreign firms) increase import price inflation.

In the empirical strand of the literature, several papers attempt to measure the pass-through from supply chain disruptions to prices. LaBelle and Santacreu, 2022 find that exposure to foreign shocks through global value chains has a negative and significant effect on output and employment—increasing month-over-month backlogs by 1 percent increases the industry inflation rate by 0.24 percentage points, while the same increase for delivery times causes an increase of about 0.26 percentage points. In their report from November 2021, Amiti, Heise, Wang, et al. (2021) find that a 10 percent increase in import prices leads to a 2.6 percent increase in PPI post-COVID versus a 1 percent increase pre-COVID. Finally, using their Global Supply Chain Pressure Index (GSCPI), which combines information on maritime and air freight costs with country-level manufacturing, Abbai et al. (2022) find that there is a correlation between the GSCPI and different international consumer price indexes and PPI. We build on this work by using a novel dataset of shipping prices by source country to build commodity-specific measures of exposure to the increase in shipping costs.

The rest of this article is organized as follows. Sections 2 and 3 explain our data and methodology. Section 4 presents our main findings analyzing the pass-through from shipping costs to import prices. Section 5 uses results from the previous sections to calculate a range for the impact of shipping costs on import price inflation and producer price inflation. Section 6 concludes.

2. DATA

In this section, we describe the various data sources we use and how we combine them. A key limitation to our approach is that the data on import price inflation vary at the commodity level, while the data on shipping prices are at the country level. Therefore, it is not obvious how to combine the two sources of information. Ideally, we would like to know the extent to which a commodity is exposed to the increase in shipping costs, but we only know the extent to which imports from a given country are exposed to the rise in shipping costs. To circumvent this problem, we use additional data on trade flows available at the commodity by country level. After discussing the details of the various data sources in this section, we define our measure of shipping costs in Section 3.

Figure 2**Annual Growth in Shipping Costs by Country**

NOTE: The figure above shows the annual increase in shipping costs for all the ports in our dataset in 2021:Q4.

2.1 Shipping Price Data

An important contribution of this article is our use of a novel dataset on the price of shipping goods to the United States. The data on shipping costs come from Drewry Shipping Consultants, who produce monthly or bimonthly time series on shipping costs between major port pairs across the globe since 2006. Its Container Freight Rate Index represents an all-in spot-market rate that includes all maritime charges at the origin and destination ports. These charges include the base rate, fuel surcharge, and the terminal handling charge for a 40-foot-equivalent dry container of goods.

The list of port pairs included in this article is in Appendix 2.1. For countries without ports in the dataset, we use our best judgment to match them with neighboring ports. For example, we map Ireland to the U.K. port. The port-to-country crosswalk is found in Appendix 2.2 in Table 16. For all the ports, we collapse them to a quarterly level by taking the mean of all the shipping costs in that quarter before mapping each series from a destination country to the United States over time.

Figure 2 shows the growth in shipping costs between 2020 and 2021 between various countries to the United States. The change in shipping costs varies substantially across countries, with Brazil and Thailand experiencing the largest growth in 2021 and Mexico, Australia, and South Africa seeing very small increases. The cross-country variation in the change in shipping costs allows us to examine the impact of shipping costs on commodity prices based on the countries from which those commodities are imported.

2.2 Import Data

We use several data sources to gather information on import prices, shipping methods, and import volumes. Annual import volumes by commodity type and partner country come from Comtrade. We use these data to create our measure of exposure to increases in shipping costs by commodity type.

We then supplement our dataset with information on the quantity and cost of goods shipped by sea from the United Nations Conference on Trade and Development (UNCTADstat), which is available only in 2016. UNCTADstat has information at the six-digit Harmonized System (HS6) code level about the volume and the cost of goods shipped between countries by different methods of transport, including air, rail, road, and sea. For each country-good pair, we sum the value of goods shipped by all methods and create the share of the

Table 1**Shares Shipped by Different Transport Types**

Average Share of Goods Shipped by Transport Type					
	Mean	Median	SD	Minimum	Maximum
Sea	0.529	0.510	0.154	0.010	0.902
Road	0.113	0.019	0.166	7.10e-08	0.849
Air	0.269	0.275	0.166	0.0002	0.688
Railway	0.089	0.047	0.107	1.57e-07	0.491
Commodity types	86				

NOTE: The shares are calculated using the final merged dataset described below in Section 3.2. For each HS6-level product type, we sum the value of that product type shipped by each of the transport types to create an overall measure of the value of goods shipped for commodity. The value for each transport type is then divided by the sum.

Table 2**Top and Bottom 5 Product Types, by Share Shipped by Sea**

Top 5 Product Types		Bottom 5 Product Types	
Product Type	Share Shipped by Sea	Product Type	Share Shipped by Sea
Beverages and spirits	0.886	Vegetables	0.0998
Meat	0.883	Medical instruments	0.281
Iron and steel	0.859	Edible fruit and nuts	0.317
Coffee, tea, and spices	0.781	Pharmaceutical products	0.418
Inorganic chemicals	0.779	Copper and copper goods	0.437

NOTE: This table shows the HS2-level products with the highest and lowest share shipped by sea across the final merged dataset. The mean share shipped by sea across the top five commodities is approximately 84 percent, versus 53 percent in the overall dataset.

value for that good that is shipped by each method. In Section 4, we use these shares to test whether shipping prices are more important for goods that are more reliant on sea transportation. In the UNCTADstat, each good has information on the transport cost and the value of the good shipped by that transport type once it reaches its destination. We use this data to calculate a ratio of the transport cost to the value of the good.

Table 1 shows summary statistics on the share of value shipped by each transport type across HS6 commodities. On average, across product types, about 53 percent of value is shipped by sea compared with 27 percent by plane, 11 percent by road, and 9 percent by railroads. Table 2 lists the commodities with the highest and lowest value shipped by sea. The highest value shipped by sea includes beverages and spirits, packaged meats, and coffee. These are generally nonperishable items that are sourced from countries with which the U.S. does not share a border, such as Brazil for coffee and Russia for iron. The bottom five include products like fresh fruits and vegetables, for whom the U.S.'s biggest trade partner is Mexico and with whom other options such as road and railway exist.

2.3 Import Prices

The data on import prices at the HS code level come from the BLS Import Price Indexes. The import prices are monthly unadjusted import prices at the HS2 or the HS4 level, representing prices at the level of a product or a category of commodities. The data are then collapsed to a quarterly level for HS2 and HS4 commodities. Table 3 displays summary statistics for the annual growth in import prices before and during the COVID-19

Table 3
Import Price Inflation Pre-Pandemic versus Pandemic

Import Price Inflation			
Mean	All Commodities	75th Percentile Sea	75th Percentile Air
Pre-pandemic	1.304	2.233	-0.098
Pandemic	6.680	7.843	2.143
Median			
Pre-pandemic	0.264	0.995	-0.254
Pandemic	1.761	2.203	0.755
Standard Deviation			
Pre-pandemic	10.852	12.056	4.388
Pandemic	18.267	16.859	10.608

NOTE: The statistics are calculated using the raw UNCTADstat merged with raw import prices from the BLS, described below. Pre-pandemic is defined as 2011:Q1 to 2020:Q1, while the pandemic period is from 2020:Q2 to 2021:Q4. The data are at the HS2 and HS4 levels.

pandemic for three different samples.

The import price data are then merged with the UNCTADstat data on the share of value shipped by different transport types, as described in Section 2.2. The first sample includes all of the commodities that appear in the UNCTADstat data and the BLS import price series. The second sample includes all commodity types with a share shipped by sea above the 75th percentile, and the third has a share shipped by air above the 75th percentile. The mean, median, and standard deviation of all categories increased during the pandemic. However, commodities shipped by sea increased in price by 7.8 points, while commodities shipped by air only increased by about 2.1 points.

2.4 Combining the Data Sources

To measure the pass-through of shipping costs to prices in the United States, we must combine the shipping cost index, import prices, import volumes, and product-level shares shipped by sea. To begin, we merge the quarterly HS4 import prices with the shipping cost exposure index described above. We also linearly interpolate any missing shipping cost index values if the preceding and following shipping cost index values are nonmissing. Then we merge in the share of value shipped by different transport types and annual import volumes from Comtrade. After saving the data that merge at the four-digit level, we repeat the process for two-digit sectors and any commodities that do not merge for four-digit values. Finally, we drop any goods in category 27, which represents fuel products, and merge in quarterly Brent crude oil prices per barrel. The regression results controlling for oil prices are in Appendix 1.1.

3. METHODOLOGY

3.1 Measure of Exposure to Shipping Price Increase

We are trying to determine the impact of shipping costs on price inflation for an average product. To do this, we need a measure of shipping cost exposure by product. We combine the quarterly country-level shipping cost data with the annual Comtrade data on import volumes. For each commodity ω , we calculate a measure of shipping cost exposure as

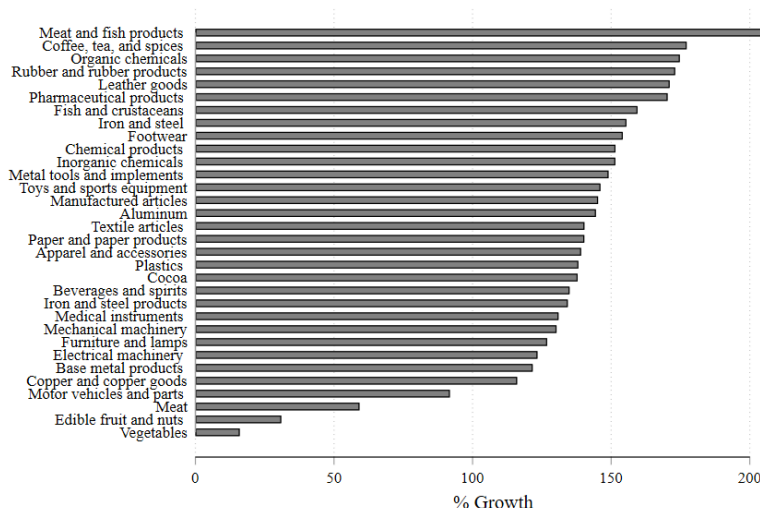
$$(1) \quad S_{t,\omega} = \sum_j \frac{R_{j,t} - R_{j,t-1}}{R_{j,t-1}} \gamma_{j,t-1}(\omega),$$

Table 4
Shipping Cost Exposure Pre-Pandemic versus Pandemic

Shipping Cost Exposure	Mean	Median	SD	Min	Max	Commodities
Pre-pandemic	4.313758	2.140413	21.84416	-51.40384	112.6588	1,316
Pandemic	85.85074	79.43548	66.8617	-23.56436	327.7778	1,311

NOTE: The statistics are calculated using the shipping cost exposure measure from Comtrade before it is merged into the other pieces of the dataset. Pre-pandemic is defined as 2011:Q1 to 2020:Q1, while the pandemic period is from 2020:Q2 to 2021:Q4. The shipping cost growth is at the HS2 and HS4 levels combined.

Figure 3
Annual Growth in Shipping Cost Exposure by Commodity in 2021:Q4



NOTE: The figure displays the annual growth in shipping cost exposure for all HS2-level commodities in our dataset in 2021:Q4.

where $R_{j,t}$ is the price of shipping from country j to the U.S. at time t and $\gamma_{j,t-1}(\omega)$ is country j 's import share of good ω . We use the lagged values for import shares so that substitution between routes does not bias the price increase. $S_{t,\omega}$ is intended to measure a commodity's exposure to a shipping price shock. Next, we merge our data on the commodity-level shipping exposure measure with import price data from the BLS to create a quarterly dataset of shipping cost exposure and price increases.

Table 4 shows summary statistics for the pre-pandemic and pandemic values of shipping cost exposure as measured in Equation 1. Pre-pandemic, the typical annual growth in shipping costs was around 4 percent. During the pandemic, shipping costs spiked—on average across commodity types, companies saw an 85 percent growth in the cost of shipping goods with one type of product experiencing a maximum 327 percent growth in shipping cost exposure.

Figure 3 displays the growth rate in shipping costs for all HS2-level commodities between 2020:Q4 and 2021:Q4. All product types have seen increases in shipping cost exposure throughout 2021. The smallest growth in shipping costs have been seen for meat, fruits and nuts, and vegetables. Both fruits and nuts and vegetables have a large portion of their value coming to the U.S. from Mexico, a country that mainly sends goods to the U.S. by roads and by railway. Meat, instead, has imports mostly from Australia and New Zealand. Australia and New Zealand, in turn, saw some of the lowest shipping cost increases in 2021, as seen in Figure 2. In contrast, meat and fish products, such as caviar, sausages, and canned products, and coffee, tea, and spices saw the largest increase in shipping cost exposure. Meat and fish products come largely from Thailand and

Indonesia, while coffee, tea, and spices come from Vietnam and Brazil.

3.2 Measuring the Pass-Through of Shipping Costs to Prices

Next, we run an ordinary least squares regression of import price inflation on our measure of shipping cost exposure. We estimate the following equation:

$$(2) \quad \pi_{it} = \beta S_{it} + f_i + \epsilon_{it},$$

where π_{it} is the annual growth in import prices, S_{it} is the annual growth in shipping cost exposure defined in Equation 1, and f_i is a set of commodity-level fixed effects. Our coefficient of interest is β , which gives the percentage point increase in import price inflation associated with a 1-percentage-point increase in our measure of exposure to shipping price growth.

One concern is that the error term will be correlated over time if changes to import prices and shipping costs are persistent. To address this issue, we adjust the standard errors for panel-specific AR1 autocorrelation. Panel-specific AR1 errors adjust the standard errors for correlation between a period and the period before within a specific commodity. We also adjust the standard errors to allow for within-period correlation across goods.

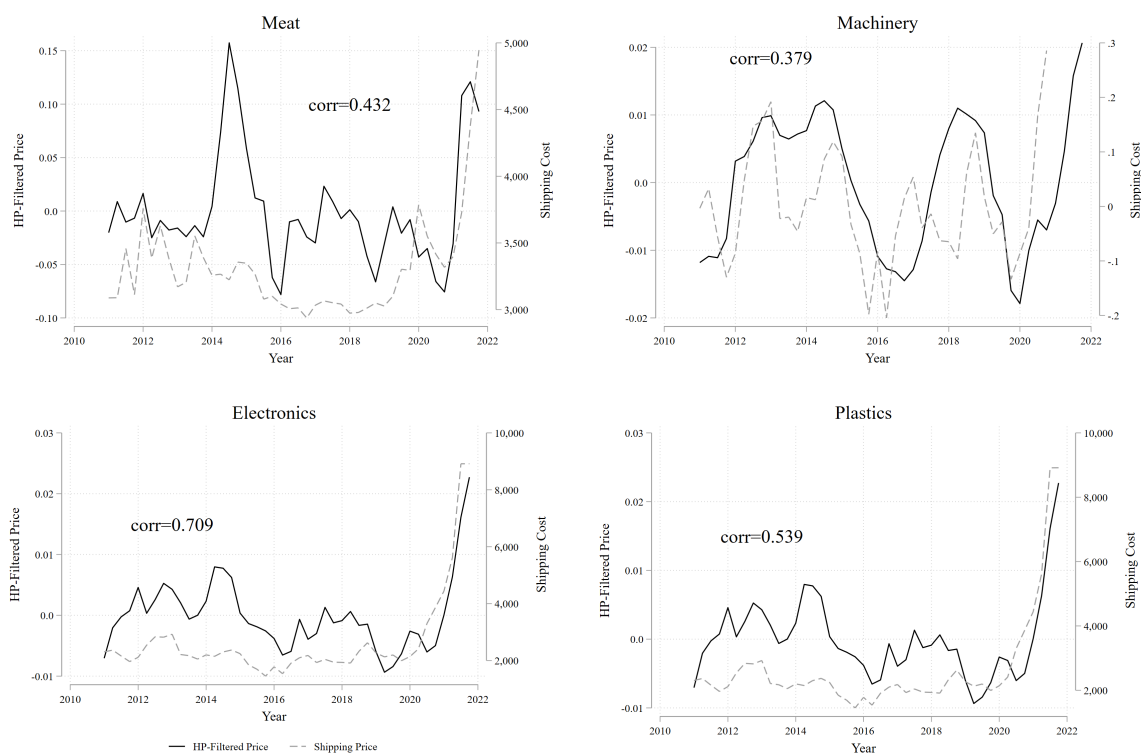
One possibility is that the measure of shipping cost exposure is capturing broader pandemic disruptions such as factory closures due to COVID-19 outbreaks. This would be the case if countries that experienced the biggest increase in shipping costs also had the most stringent lockdown measures or the most severe outbreaks. Looking at Figure 2, there does not seem to be a pattern between the growth in shipping costs and other pandemic factors. For example, Brazil experienced the largest increase in shipping costs while also enacting very few pandemic-related shutdowns. On the other hand, Australia had very stringent COVID-19 policies but a much smaller increase in shipping costs. However, we exploit heterogeneity in the share of the value of each commodity shipped by sea and heterogeneity across the types of commodities to provide suggestive evidence that the role of shipping costs is particularly important.

4. RESULTS

Before we turn our attention to the regression results from estimating Equation 2, we first examine the time-series correlation between import prices and our measure of shipping price exposure for a few select HS2 commodities. Figure 4 displays time-series plots of shipping price exposure (in gray) and the cyclical component of the HP-filtered import prices (in black) for each of the four good types. Each plot also displays the correlation between the two values over the entire period in the figure. In each case, the shipping cost exposure and import prices are correlated from 2010 to 2021, the period on which we are focused. For each commodity, import price inflation and shipping cost exposure both increase around the same time in the middle of 2020. One concern is that this correlation might be driven by the spike in both import prices and shipping costs during the pandemic. The figure note gives the correlation for the time period before the pandemic, and in each case there is still a significant correlation between the two series. Electronics has the highest correlation over the entire period, while machinery has the highest pre-pandemic correlation values.

Now we turn to the results of our formal regression analysis. Table 5 shows the results of estimating Equation 2 across several specifications. We use the data from all matched HS commodities, but in Appendix 1.3 the tables are repeated for only two-digit HS codes. Our baseline result is in Column 1, which uses the full sample. Import price inflation for goods that were exposed to a 1-percentage-point higher increase in shipping price growth was on average 0.0247 percentage points higher.

Next, in Columns 2 and 3, we split the data into the time before and the time after the pandemic. Before the pandemic, we find that the correlation between shipping price growth and import price growth was insignificant. From Figure 4, there is clearly a significant correlation between shipping costs and inflation for a

Figure 4**Time Series of Prices and Shipping Costs for Specific Commodities**

NOTE: The figure shows the value of HP-filtered import prices as a solid line, while the dotted gray line displays the value of shipping cost exposure for specific HS2- and HS4-level commodities. The correlation displayed in the figure is the overall correlation, but the pre-pandemic correlation levels for meat, machinery, electronics, and plastics are 0.238, 0.514, 0.397, and 0.277, respectively.

few select commodities even before the pandemic. But the regression analysis suggests that this does not hold on average across commodity types. This is consistent with the idea that the pass-through is small and shipping prices were relatively small and stable.

After the pandemic, the pass-through has been much larger. Shipping price growth that is 1 percentage point higher is associated with import price inflation that is 0.0684 percentage points higher. This might seem modest, but when one considers the magnitude of the shipping price increase post-pandemic, the cost of shipping can account for a substantial portion of import price inflation. From Table 4, the average growth in shipping cost was 85.85 percent. This would imply import price inflation of 5.87 percentage points per year during the pandemic.

In Table 6, we restrict the commodities to those in which most of the goods are shipped by sea and those goods where the ratio of transport costs by sea to the overall value of the good is high. Isaacson and Rubinton (2022) find a relationship between the share of goods in an industry shipped by sea and import price inflation. We then replicate our baseline regressions from Table 5 with the smaller samples. The relationship between shipping cost exposure and commodity prices is stronger as we limit the sample to these types of goods. For commodities with above the 75th percentile of value shipped by sea, an increase in shipping prices is associated with a 0.117-percentage-point higher import price inflation during the pandemic. Meanwhile, having an above-median ratio of transport costs to the value of the good is associated with a pass-through rate of 0.127 in 2021. These results suggest that goods that rely more heavily on shipping saw larger price increases during the COVID-19 pandemic.

Table 5
Baseline Regression Results

	Import Price Inflation		
	Baseline	Before 2020	After 2020
	(1)	(2)	(3)
Shipping cost growth	0.0247 *** (0.00557)	0.00708 (0.00617)	0.0684 *** (0.0142)
Observations	2,950	2,334	308
R^2	0.035	0.062	0.860
Commodity fixed effects	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

Table 6
Baseline Regressions with Sample Restrictions

	Import Price Inflation, %					
	75th Percentile Share Sea			Above-Median Cost Ratio		
	Baseline	Before 2020	After 2020	Baseline	Before 2020	After 2020
	(1)	(2)	(3)	(4)	(5)	(6)
Shipping Cost Growth	0.0457*** (0.00873)	0.0237*** (0.00645)	0.117*** (0.0162)	0.0430*** (0.00896)	0.0142* (0.00849)	0.127*** (0.0165)
Observations	730	578	76	1497	1193	152
R^2	0.076	0.073	0.789	0.045	0.059	0.889
Commodity fixed effects	Y	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms. The first set of results are from those commodities with above the 75th percentile of value shipped by sea, and the second set is those with a ratio of transport costs to value of good above the median.

Table 7 shows the results of estimating Equation 2 but splitting the sample into four groups based on the type of good. Food and materials have the strongest relationship between shipping cost and price growth. The food product types include edible vegetables, dairy products, meats, and others, while materials commodities represent plastics, chemicals, oils, metals, and other raw materials for production. For a 1–percentage–point increase in the annual shipping cost growth, the price index increases by 0.056 percentage points for materials and by 0.0719 percentage points for food. On the other hand, for the group of goods classified as machines, electronics, and parts, which includes wires, conductors, microphones, and other electronic equipment, the pass-through is only 0.0105. For consumer goods, which includes miscellaneous items such as shoes, toys, clothes, sports equipment, and lamps, the pass-through is small and insignificant.

There are a number of reasons one would expect different amounts of pass-through depending on the type of good. Essentially this is a measure of how much producers are passing on their costs to their buyers. This pass-through depends on the degree of market competition and price rigidity. Furthermore, it might depend on whether goods are being sold to consumers or intermediates. Finally, in the case of shipping, it could depend on whether goods can be stored in inventory or if they are perishable. The higher pass-through in food and

Table 7
Regression Results by Type of Product

	Import Price Inflation				
	Baseline	Food	Materials	Machines, Electronics, and Parts	Consumer Goods
	(1)	(2)	(3)	(4)	(5)
Shipping cost growth	0.0247*** (0.00557)	0.0719*** (0.0223)	0.0560*** (0.0129)	0.0105*** (0.00402)	0.00489 (0.00456)
Observations	2,950	480	802	1,228	440
R^2	0.035	0.047	0.056	0.089	0.058
Commodity fixed effects	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

materials seems to suggest that the distinction between final goods and intermediates and whether or not a good is perishable might both be important factors in the extent to which shipping costs are passed through to the price.

In our baseline analysis, we did not include time fixed effects in the specification. In these regressions, the coefficient β measures whether the correlation between import price inflation and shipping costs is, on average across goods, positive. In a final version of our analysis, we add time fixed effects. In this case, we are asking a slightly different question. The coefficient β asks whether, within a period, goods that saw higher increases in shipping prices also saw higher import price inflation.

Table 8 shows the results of adding time fixed effects to Equation 2. The baseline measure with both types of fixed effects is not statistically significant—only in the period after 2020 is the relationship significant. An increase of 1 percentage point in the shipping cost exposure measure increases the import price index by 0.0419. Before the pandemic, the relationship between shipping cost and import prices could mostly be explained by commodity-level effects or by month-specific changes in prices. However, shipping costs became significant in 2021; this result is similar to that of Amiti, Heise, Wang, et al. (2021), who find that the impact of import prices on producer prices more than doubled during the pandemic period.

5. THE IMPLICATIONS OF THE SHIPPING COST SHOCK ON INFLATION

In this section, we use our estimates of the pass-through from shipping costs to import prices to produce back-of-the-envelope calculations for the impact on inflation. We find that the pass-through from shipping costs to inflation was much larger during the pandemic. Our estimates of the pass-through after 2020 range from 0.0419 in the specification with commodity and time fixed effects to 0.0684 in the specification with only commodity fixed effects. We use these estimates to produce a lower and upper bound on the effect of shipping cost exposure.

During the pandemic, the shipping cost exposure measure increased by an average of 85.85 percent per year during the period from 2020:Q2 to 2021:Q4 (see Table 4). This would imply an increase in import price inflation between 3.60 and 5.87 percentage points.³ During the two-year period between 2019:Q4 and 2021:Q4, year-over-year import price inflation averaged 5.26 percent in our sample; thus, the increase in shipping costs can account for between 68 and 111 percent of the increase in import price inflation.

3. We multiply the growth in shipping costs by the estimates of pass-through from Tables 5 and 8, 0.0684 and 0.0419, to get the estimated impact on inflation.

Table 8**Import Price Inflation over Time**

	Import Price Inflation		
	Baseline	Before 2020	After 2020
	(1)	(2)	(3)
Shipping cost growth, %	0.00585 (0.0122)	-0.0134 (0.0141)	0.0419* (0.0247)
Observations	3,250	2,562	344
R^2	0.088	0.111	0.858
Commodity fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

However, the literature has found that increases in import prices only have a limited impact on U.S. price inflation (Amiti, Redding, and Weinstein (2019) and Dellmo (1996)). Amiti, Heise, Wang, et al. (2021) estimate that during the pandemic, the pass-through from a 10 percent increase in import price inflation to PPI inflation was 2.6 percent. Over the same period from 2019:Q4 to 2021:Q4, year-over-year producer price inflation averaged 6.13 percent. Thus, shipping cost growth could account for between 15 and 25 percent of PPI inflation.

6. CONCLUSION

In this article, we investigate the relationship between shipping costs and import price inflation, especially during the COVID-19 pandemic. To examine pass-through, we create a dataset combining shipping cost data by country with information on import prices by commodity type and on import volumes by country and commodity type. After creating our measure of shipping cost exposure for different types of goods, we measure the pass-through of shipping costs to import price inflation over time. While the overall impact of shipping costs on import price inflation is modest, the overall growth in shipping costs has been so large that between 3.6 and 5.87 percentage points of import price inflation can be attributed to it. Additionally, product types with greater shares shipped by sea experience a stronger impact of shipping costs than those with a smaller share shipped by sea. Additionally, in 2021, pass-through was larger than in the period from 2010 to 2019, with differential impacts across different good types. Within different broad categories of goods, the impact of shipping costs tends to be larger for more perishable goods. Thus, recent spikes in import prices can be partially, but not entirely, attributed to the rise in shipping costs during the pandemic.

APPENDIX 1. ALTERNATE REGRESSIONS

Appendix 1.1 Controlling for Oil Prices

Table 9

Controlling for Oil Prices

2-6	Import Price Inflation				
	Baseline	Before 2020	After 2020	75% Percentile Share by Sea	Above-Median Cost Share
	(1)	(2)	(3)	(4)	(5)
Shipping cost growth	0.0241*** (0.00508)	0.00651 (0.00610)	0.0328** (0.0163)	0.0452*** (0.00845)	0.0421*** (0.00812)
Observations	2,950	2,334	308	730	1,497
R^2	0.042	0.066	0.868	0.184	0.055

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

Table 9 shows the results of the baseline regressions above with Brent crude oil prices added as a control. The columns show results for a regression of the annual growth in import price inflation on the annual growth in shipping prices, controlling for oil prices and commodity fixed effects. The second column restricts to the period before 2020 and the third column shows results for after 2020. Then, for the last two columns, the sample is limited to those commodities with above the 75th percentile of the value of goods shipped by sea and above-median share of costs from shipping respectively. The baseline regression, before 2020 regression, and the above-median cost share regression coefficients are all similar to the original results without controlling for oil prices. However, for the sample after 2020, the coefficient is roughly half as large as it is in the baseline regressions in Table 5. The coefficient for goods with above the 75th percentile of value shipped by sea is much larger than it is in Table 6.

Appendix 1.2 Sample Restrictions with Time Fixed Effects

Table 10 shows the results from Table 6 with additional time fixed effects. Controlling for time fixed effects reduces the magnitude and significance of the effect of shipping costs for goods with a large share of value shipped by sea. There is no statistically significant pass-through of shipping costs overall or before 2020, and the pass-through after 2020 is about half of its value without controlling for time fixed effects. The impact is similar for the above-median cost ratio commodities.

Appendix 1.3 Regression Results for HS2 Commodities Only

The tables below replicate the main regression results using HS2-level commodities only. Table 11 replicates Table 5 above. The magnitude of the impact of shipping costs on import price inflation is, for the most part, larger for the broader sectors of goods. The significance also either improved or stayed consistent. For HS2 commodities, the baseline measure of pass-through of shipping prices to import prices is 0.041. The same patterns hold for the results in Table 12, with the impact of commodities above the 75th percentile in share shipped by sea increasing by 0.08. Table 13 shows the HS2 results for specific good types. Food, Materials, and Machinery all remained significant, while Consumer Goods remained not statistically significant. The coefficients on food and materials remained approximately the same, while pass-through for materials increased sharply.

Tables 14 and 15 add time fixed effects to the HS2 regressions above. Table 14 replicates Table 8 above and Table 15 replicates Table 10 in the Appendix. While the results have shifted slightly, they are quantitatively very similar.

Table 10
Baseline Regressions with Sample Restrictions and Time Fixed Effects

2-7	75th Percentile Share Sea			Above-Median Cost Ratio		
	Baseline (1)	Before 2020 (2)	After 2020 (3)	Baseline (4)	Before 2020 (5)	After 2020 (6)
Shipping Cost Growth	-0.00440 (0.0119)	-0.0187 (0.0124)	0.0594* (0.0313)	0.0117 (0.0200)	-0.0241 (0.0212)	0.0693** (0.0302)
Observations	730	578	76	1497	1193	152
R^2	0.288	0.249	0.821	0.137	0.122	0.899
Commodity fixed effects	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

Table 11
Baseline Regressions: HS2 Sample

2-4	Import Price Inflation		
	Baseline (1)	Before 2020 (2)	After 2020 (3)
Shipping cost growth	0.0408*** (0.00750)	0.0187* (0.00954)	0.117*** (0.0177)
Observations	1,280	1,024	128
R^2	0.040	0.065	0.857
Commodity fixed effects	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

Table 12
Baseline Regressions with Sample Restrictions for HS2 Commodities

2-7	75th Percentile Share Sea			Above-Median Cost Ratio		
	Baseline (1)	Before 2020 (2)	After 2020 (3)	Baseline (4)	Before 2020 (5)	After 2020 (6)
Shipping cost growth	0.0880*** (0.0152)	0.0408** (0.0175)	0.195*** (0.0225)	0.0573*** (0.0119)	0.0290 (0.0181)	0.176*** (0.0250)
Observations	320	256	32	640	512	64
R^2	0.114	0.045	0.828	0.041	0.062	0.833
Commodity fixed effects	Y	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

Table 13
Regressions by Product Type: HS2 Sample

2-6	Import Price Inflation				
	Baseline	Food	Materials	Machines, Electronics, and Parts	Consumer Goods
	(1)	(2)	(3)	(4)	(5)
Shipping cost growth	0.0408*** (0.00750)	0.0720*** (0.0201)	0.0982*** (0.0146)	0.0130*** (0.00283)	0.00378 (0.00428)
Observations	1,280	320	480	240	240
R^2	0.040	0.040	0.132	0.243	0.076
Commodity fixed effects	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

Table 14
Regressions with Time Fixed Effects: HS2 Sample

2-4	Import Price Inflation		
	Baseline	Before 2020	After 2020
	(1)	(2)	(3)
Shipping cost growth	0.0239 (0.0197)	-0.0117 (0.0211)	0.0800** (0.0345)
Observations	1,280	1,024	128
R^2	0.108	0.109	0.852
Commodity fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

Table 15
Baseline Regressions with Sample Restrictions with Time Fixed Effects for HS2 Commodities

2-7	75th Percentile Share Sea			Above-Median Cost Ratio		
	Baseline (1)	Before 2020 (2)	After 2020 (3)	Baseline (4)	Before 2020 (5)	After 2020 (6)
Shipping cost growth	-0.00606 (0.0181)	-0.0225 (0.0237)	0.0896* (0.0459)	0.0385 (0.0289)	-0.0355 (0.0363)	0.114** (0.0490)
Observations	320	256	32	640	512	64
R^2	0.388	0.298	0.859	0.140	0.118	0.838
Commodity fixed effects	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE: Standard errors are adjusted for heteroskedasticity, within-period correlation, and panel-specific serially correlated error terms.

APPENDIX 2. PORT INFORMATION**Appendix 2.1 List of Port Pairs**

1. Australia (Melbourne) to LA
2. Bangladesh (Chittagong) to NY
3. Brazil (Santos) to Houston
4. Central China (Shanghai) to LA
5. Hong Kong to LA
6. India (Nhava Sheva) to NY
7. Indonesia (Jakarta) to LA
8. Israel (Ashdod) to NY
9. Japan (Yokohama) to LA
10. Korea (Busan) to LA
11. Malaysia (Tanjung Pelepas) to LA
12. New Zealand (Auckland) to LA
13. N. Europe (Rotterdam) to NY
14. Philippines (Manila) to LA
15. Poland (Gdansk) to NY
16. Russia (St. Petersburg) to NY
17. Singapore to LA
18. South Africa (Durban) to NY
19. Sweden (Gothenburg) to NY
20. Taiwan (Kaohsiung) to LA
21. Thailand (Laem Chabang) to LA
22. Turkey (Istanbul) to NY
23. U.A.E (Jebel Ali) to NY
24. U.K. (Felixstowe) to NY
25. Vietnam (Ho Chi Minh) to LA
26. West Mediterranean (Genoa) to NY

Appendix 2.2 Crosswalk**Table 16****Crosswalk from Country to Ports**

Port	Countries
Australia	Australia
New Zealand	New Zealand
Brazil	Brazil, Argentina, Uruguay, Bolivia
China	China
India	India, Bangladesh
Indonesia	Indonesia
Japan	Japan
Korea	Korea
Mexico	Mexico, Guatemala, Belize, Nicaragua
Northern Europe	Austria, Belgium, Bulgaria, Czech Republic, Germany, Switzerland,
Northern Europe (cont.)	Estonia, Finland, Hungary, Lithuania, Luxembourg, Iceland,
Northern Europe (cont.)	Latvia, The Netherlands, Romania, Slovakia, Slovenia, Sweden
Russia	Russia, Ukraine
Taiwan	Taiwan
Turkey	Turkey
Great Britain	Great Britain, France, Spain, Ireland, Portugal
West Mediterranean	Cyprus, Greece, Croatia, Italy, Malta
Hong Kong	Hong Kong
Vietnam	Vietnam
Singapore	Singapore
Thailand	Thailand
Malaysia	Malaysia
Philippines	Philippines
Egypt	Egypt
South Africa	South Africa
United Arab Emirates	United Arab Emirates
Israel	Israel

REFERENCES

- Abbai, Belai, Ozge Akinci, Gianluca Benigno, Julian di Giovanni, Jan JJ Groen, Ruth Cesar Heymann, Lawrence Lin, Adam I Noble, et al. 2022. *The global supply side of inflationary pressures*. Technical report. Federal Reserve Bank of New York.
- Amiti, Mary, Sebastian Heise, Aidan Wang, et al. 2021. *High import prices along the global supply chain feed through to us domestic prices*. Technical report. Federal Reserve Bank of New York.
- Amiti, Mary, Stephen J Redding, and David E Weinstein. 2019. The impact of the 2018 tariffs on prices and welfare. *Journal of Economic Perspectives* 33 (4): 187–210.
- Comin, Diego A, and Robert C Johnson. 2021. *Supply chain constraints and inflation*. Technical report. Manuscript.
- Dellmo, Hans. 1996. Relationships between swedish producer and import prices and. *Economic report of the president, april*. 2022. Transmitted to Congress. <https://www.whitehouse.gov/wp-content/uploads/2022/04/ERP-2022.pdf>.
- Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning. 2021. Monetary policy in times of structural reallocation. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, nos. 2021-111.
- Isaacson, Maggie, and Hannah Rubinton. 2022. Inflation and shipping costs. *Economic Synopses*, no. 5.
- LaBelle, Jesse, and Ana Maria Santacreu. 2022. Global supply chain disruptions and inflation during the covid-19 pandemic. *Federal Reserve Bank of St. Louis Review*.
- Leibovici, Fernando, and Jason Dunn. 2021. Supply chain bottlenecks and inflation: the role of semiconductors. *Economic Synopses*.
- Leibovici, Fernando, and Ana Maria Santacreu. 2015. International trade fluctuations and monetary policy. *Available at SSRN 2657467*.
- Smialek, Jeanna, and Eshe Nelson. 2021. The world's top central bankers see supply chain problems prolonging inflation. *New York Times*, <https://www.nytimes.com/2021/09/29/business/central-bankers-supply-chains-inflation.html>.
- Soyres, Francois de, Ana Maria Santacreu, and Henry Young. 2022. Fiscal policy and excess inflation during covid-19: a cross-country view.
- Swanson, Ana. 2022. The world's top central bankers see supply chain problems prolonging inflation. *New York Times*, <https://www.nytimes.com/2022/01/12/business/inflation-supply-chain.html>.
- Wei, Shang-Jin, and Yinxi Xie. 2020. Monetary policy in an era of global supply chains. *Journal of International Economics* 124:103299.

External Shocks versus Domestic Policies in Emerging Markets

Emilio Espino, Julian Kozłowski, Fernando M. Martin, and Juan M. Sánchez

Abstract

Debt crises in emerging markets have been linked to large fiscal deficits, high inflation rates, and large devaluations. This article studies a sovereign default model with domestic fiscal and monetary policies to understand Argentina's experience during the 2000s commodity boom (2005–2017), following the default of 2001. The model suggests that domestic policies played a critical role in Argentina's poor economic performance. Despite exceptionally favorable terms of trade, a rise in government spending led to higher taxation, inflation and currency depreciation, and lower output. Economic performance would have been worse had Argentina followed a strict, rather than accommodative, monetary policy without curbing its expansionary fiscal policy. Finally, limited access to international credit markets during this episode did not appear to play a significant role.

JEL codes: E52, E62, F34, F41, G15

Federal Reserve Bank of St. Louis *Review*, Second Quarter 2023, 105(2), pp. 108–21.
<https://doi.org/10.20955/r.105.108-121>

1. INTRODUCTION

Inflation, exchange rates, and fiscal deficits play key roles in sovereign debt crises. Revisiting the history of Latin America, Kehoe, Nicolini, and Sargent (2020) argue that “despite their different manifestations, all economic crises in Latin America have been the result of poorly designed or poorly implemented macro-fiscal policies.” On the other hand, there is a long tradition connecting domestic economic performance to external factors. For example, Drechsel and Tenreyro (2017), Fernández, Schmitt-Grohé, and Uribe (2017) and Fernández, González, and Rodríguez (2018) find a significant contribution of commodity price shocks to output fluctuations.

In this article, we contribute to the classic debate on whether external factors or domestic policies explain the poor economic performance of emerging countries. To this effect, we study the experience of Argentina following the default of 2001, specifically between 2005 and 2017. Two driving forces, favorable terms of trade, and an increase in government expenditure go a long way in explaining the country's macroeconomic performance during that period. Our exercise suggests that government expansion accounted for the rise in taxation, inflation, and currency depreciation and kept output growth low, countering the benign effects of favorable terms of trade. We also argue that following a strict monetary policy, though potentially successful in containing inflation and currency depreciation, would have been detrimental without addressing the rise in spending. Finally, we find that varying Argentina's access to international credit markets does not alter the story significantly.

Emilio Espino is an associate professor of economics at Universidad Torcuato Di Tella. Julian Kozłowski is a senior economist, Fernando Martin is an assistant vice president and economist, and Juan M. Sánchez is a vice president and economist at the Federal Reserve Bank of St. Louis. The authors thank Rody Manuelli for valuable comments and Samuel Jordan-Wood, Marco Spinelli, and Olivia Wilkinson for research assistance.

©2023, Federal Reserve Bank of St. Louis. The views expressed in this article are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Articles may be reprinted, reproduced, published, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. Abstracts, synopses, and other derivative works may be made only with prior written permission of the Federal Reserve Bank of St. Louis.

Our analysis employs the framework developed by Espino, Kozlowski, Martin, and Sanchez (2022, hereafter EKMS). The economy is a version of a tradable–nontradable (TNT) small open economy (as in Uribe and Schmitt-Grohé, 2017, §8), extended to include production, money, and sovereign default. The government makes transfers and provides a public good, and it obtains resources from labor taxes, money creation, and external debt issued in foreign currency. Each period, the government may choose to repudiate the debt, at the cost of temporary exclusion from international credit markets and lower productivity. Importantly, the government lacks the ability to commit to future policies.

The experience of Argentina from 2005 to 2017 allows us to use the model to shed light on the debate of the role of external factors and government policy in explaining macroeconomic outcomes. During this period, Argentina experienced favorable terms of trade due to a global boom in commodity prices. At the same time, government spending grew considerably and taxation and inflation rose significantly. In our analysis, we take the term-of-trade boom and the rise in government spending as given and let the model predict debt, taxes, inflation, currency depreciation, and output. We also conduct several counterfactuals to understand the role of exogenous and endogenous factors.

We obtain four main results. First, our model simulations imply that the rise in government spending, coupled with an accommodative monetary policy, was the main driver of higher taxation and inflation and lower output. In other words, domestic policy was to blame for Argentina’s poor economic performance. Absent the expansion of government, the boom in commodity prices would have implied a rise in real output.

Second, the interaction of fiscal and monetary policies played an important role. If Argentina had followed a strict monetary policy by fixing the money growth rate, inflation would have been contained at the cost of even higher taxation. The result would have been lower output. One could further conjecture that an unwillingness to raise taxes to accommodate a strict monetary policy in this counterfactual scenario might eventually lead to debt crisis.

Third, the simulations and counterfactuals suggest that the boom in commodity prices might have facilitated the rise in government spending. In our benchmark scenario, inflation rises 10 percentage points between 2006 and 2012, which closely matches the experience for Argentina. In the absence of a commodity boom, the increase in inflation would have been 15 percentage points. Similarly, gross domestic product (GDP) expressed in US dollars would have decreased rather than increased and would have limited Argentina’s ability to borrow internationally when it reentered credit markets in full in 2016.

Finally, we find that exclusion from international credit markets did not play a major role in explaining domestic policies or macroeconomic performance. We show this result by running a counterfactual in which the government gains full access to international debt markets in 2005 instead of 2016. Although the government would have used debt upon reentry (driving the debt-to-GDP ratio to be 10 percentage points larger by 2016), the evolution of the model’s main variables is affected in only a minor way. However, we find that earlier debt accumulation would have lowered Argentina’s capacity to handle the adverse shock to its terms of trade that occurred in 2013.

The rest of the article is structured as follows. Sections 2 and 3 describe the model and its calibration, respectively. Section 4 details the main analysis, which studies the case of Argentina in 2005–2017. Section 5 concludes.

2. MODEL

In this section we briefly describe the main ingredients of the model. For a full characterization and analytical results, see EKMS.

Preferences, Endowments, and Technology. A large number of identical infinitely lived agents live in a small open economy. A nontradable good is produced (y^N), and it is consumed domestically (c^N) and is also used as the only input by the government to produce a one-to-one public good, g . A tradable good is imported for domestic consumption (c^T) but cannot be produced locally. Finally, another tradable good is produced domestically (y^T) and is exported for foreign consumption.

The representative household has one unit of time each period to use for leisure, ℓ , or work, h . Thus, $\ell + h = 1$. A time-separable, expected discounted utility function represents preferences. Let the period utility be given by

$$u(c^N, c^T) + v(\ell) + \vartheta(g),$$

where u , v , and ϑ are strictly increasing, strictly concave, C^2 , and satisfy standard boundary conditions. Agents discount the future by factor $\beta \in (0, 1)$.

An aggregate production technology transforms hours worked, h , into nontradable output, y^N , and exported goods, y^T . This technology can be represented by a cost function $F : \mathbb{R}_+^2 \rightarrow \mathbb{R}_+$, which is strictly increasing, strictly convex, and homogeneous of degree 1. Given h , feasible levels of (y^N, y^T) must satisfy

$$(1) \quad F(y^N, y^T) - h \leq 0.$$

The technological possibilities described by F will depend on the government's default decision. Specifically, there will be a productivity penalty while the country is excluded from international credit markets due to past default. This dependence is omitted here for convenience, and we specify it explicitly in Section 3.

Market Structure. Agents can exchange tradable and nontradable goods and domestic currency (fiat money). The international price of exported goods, p^T , is exogenous and denominated in dollars, while the international price of imported goods is assumed to be 1. Thus, p^T is also the terms of trade. Nominal variables, normalized by the stock of the aggregate supply of money, are domestic prices p^N , wages w , exchange rate (units of domestic currency per unit of foreign currency) e , and money holdings m . The growth rate of the money supply is represented by μ .

Households must use cash to purchase nontradable goods, so they face the cash-in-advance constraint

$$(2) \quad p^N c^N \leq m.$$

This constraint implies that (normalized) expenditure on nontradable goods, $p^N c^N$, cannot exceed (normalized) money holdings at the beginning of the period, m .

Government Budget Constraint. Government uses of funds consist of (i) endogenous government purchases, g ; (ii) exogenous lump-sum nonnegative transfers to households, γ (expressed in units of the nontradable good); and (iii) payments of maturing external debt, B . The government has three sources of funds at its disposal: (i) endogenous labor income taxes, τ ; (ii) endogenous growth of the money supply or seigniorage, μ ; and (iii) one-period external debt denominated in foreign currency, B' . New debt is issued to international lenders at discount price Q . The government budget constraint, expressed in units of local currency, is then

$$(3) \quad p^N(g + \gamma) + eB \leq \tau wh + \mu + eQB'.$$

Note that external debt payments and issuance is multiplied by the exchange rate since debt is denominated in foreign currency.

Balance of Payments Constraint. The relationship of the country with the rest of the world must satisfy the following balance of payments constraint:

$$(4) \quad p^T y^T - c^T = B - QB',$$

where the left-hand side represents the trade balance and the right-hand side net-external borrowing. Note that the balance of payment is expressed in units of foreign currency.

If we combine (3) and (4), we can express the government budget constraint as the relationship between the external sector (the trade balance) and the public sector (the primary surplus plus seigniorage):

$$(5) \quad \tau wh - p^N(g + \gamma) + \mu - e(p^T y^T - c^T) \geq 0.$$

International Lenders. The debt prices used in equations (3) and (4) are determined by risk-neutral international lenders. They must make zero-expected profits in equilibrium. The price of debt $Q(B', s)$ depends both on the amount borrowed, B' , and the exogenous state of the economy, s . The state s may include any variable that evolves over time, e.g., the terms of trade, p^T . The zero-profit condition implies the following functional equation for debt prices:

$$(6) \quad Q(B', s)B' = \frac{\mathbb{E}[\mathcal{P}(B', s')|s]B' + \mathbb{E}[(1 - \mathcal{P}(B', s'))Q^d(s')|s]B^d}{1 + r}.$$

Here, \mathcal{P} represents the repayment probability (explained below); B^d is the renegotiated level of debt, which is exogenous; and $Q^d(s')$ stands for the price of debt in default. The first term in (6) represents the expected value

in case of repayment and the second term the expected value in case of default. The price of debt in default must satisfy

$$Q^d(s') \equiv \delta Q(B^d, s') + \frac{(1 - \delta)\mathbb{E}[Q^d(s'')|s']}{1 + r}.$$

The Representative Firm and the Resource Constraint. Local firms hire domestic labor at wage w to produce nontradable and tradable goods using the technology F . The assumption that there are constant returns to scale implies that the industry behaves as if there were a representative firm solving

$$\max_{y^N, y^T, h} \{p^N \gamma^N + ep^T \gamma^T - wh\},$$

subject to (1).

Since households are identical, c^N , c^T , and h are also aggregate quantities. Thus, the resource constraint in the nontradable sector is

$$(7) \quad c^N + g = y^N.$$

Representative Household. The decisions made by households depend on aggregate and individual state variables. First, there are endogenous state variables, which depend on government choices: the beginning-of-period government debt, B , and the current default decision, \mathcal{I} . Next, there is the exogenous state of the economy, represented by s , which includes any variable that varies over time (for example, export prices p^T). Finally, the individual state variable is the household's (normalized) money balances at the beginning of the period, m . Also note that households know the evolution of all aggregate variables and how prices and policies depend on the aggregate state.

The household budget constraint is given by

$$(8) \quad p^N c^N + ec^T + m'(1 + \mu) \leq (1 - \tau)wh + m + p^N \gamma.$$

The left-hand side of the household budget constraint represents the expenses in nontradable ($p^N c^N$) and imported consumption (ec^T), and money holdings for the next period ($m'(1 + \mu)$). The right-hand side represents its resources: labor income net of taxes ($(1 - \tau)wh$), money holdings (m), and transfers ($p^N \gamma$).

The household's problem is given by

$$V(m, B, \mathcal{I}, s) = \max_{(c^N, c^T, m', h)} u(c^N, c^T) + v(1 - h) + \vartheta(g) + \beta \mathbb{E}[V(m', B', \mathcal{I}', s')|B, \mathcal{I}, s],$$

subject to (2) and (8), and where $V(m, B, \mathcal{I}, s)$ represents the value for a household starting the period with individual (normalized) money holdings m and aggregate state (B, \mathcal{I}, s) .

Government Problem. At the beginning of each period, once the exogenous state s is realized, the government chooses between default and repayment. If it decides to repay its debt, B , it chooses the new level of debt, B' , labor income taxes, τ , the growth rate of money, μ , and government purchases, g —recall that transfers to households, γ , are exogenous. When making these choices, the government takes into account the response of domestic firms, domestic households, and international lenders to the new set of policies. It is further restricted by the balance of payments (4), the government budget constraint (5), and the resource constraint for nontradable goods, (7).

The government takes as given how future policy will respond to future shocks and the inherited amount of debt. If the government decides to default, it is excluded from international credit markets. It regains access at the beginning of the period with probability δ with a renegotiated level of debt $B^d \geq 0$, which is exogenous. While the country is in default, it experiences a productivity penalty $\Omega(s)$ (detailed below) that depends on state s . EKMS explain how the government problem can be written recursively, using what is known as the *primal approach*, and characterize the main trade-offs faced by the government.

3. CALIBRATION

We now describe the functional forms adopted for the quantitative analysis, discuss the sources of the parameters set externally, and explain how we set the remaining parameters' values to match some relevant statistics. The calibration is similar to EKMS, so we discuss it briefly here.

3.1 Functional Forms

The utility functions for consumption and leisure are

$$\begin{aligned} u(c^N, c^T) &= \alpha^N \frac{(c^N)^{1-\sigma}}{1-\sigma} + \alpha^T \frac{(c^T)^{1-\sigma}}{1-\sigma}, \\ \nu(\ell) &= \alpha^H \frac{\ell^{1-\varphi}}{1-\varphi}, \\ \vartheta(g) &= \alpha^G \ln g. \end{aligned}$$

Under this specification, $1/\sigma$ is both the intratemporal elasticity of substitution between c^N and c^T and the intertemporal elasticity of substitution.

The function specifying how much labor is required for production is

$$F(y^N, y^T) = \frac{[(y^N)^\rho + (y^T)^\rho]^{1/\rho}}{A}.$$

Note that A represents labor productivity and ρ is the parameter determining how easy it is (in terms of labor units) to change from the production of y^N to y^T .

Finally, following Arellano, 2008, productivity in default takes the following form:

$$(9) \quad A^{def} = A \times [1 - \Omega(s)]$$

with

$$(10) \quad \Omega(s) = \max \left\{ \omega_1 + \omega_2 \left(\frac{s - \bar{s}}{\bar{s}} \right), 0 \right\}.$$

The key parameters are $\omega_1 > 0$ and ω_2 (which is a vector if there are multiple shocks). With this specification, the default cost depends on the deviation of the shock, s , from its steady-state value \bar{s} .

3.2 Exogenous Parameters

Table 1 shows the values of the parameters set externally. For most of these parameters, we follow the same strategy as in EKMS. The risk-free interest rate is 3 percent to coincide with the average real interest rate of the world since 1985 in King and Low, 2014. The value of φ to 1.50 reproduces a Frisch elasticity of one-half (on average). The parameter δ determines the length of exclusion after default. We chose $\delta = 1/6$ so that that duration is six years, in line with the length of restructuring negotiations in Das, Papaioannou, and Trebesch, 2012 and the length of exclusion after restructuring from Cruces and Trebesch, 2013.

Recall that σ captures the intratemporal elasticity of substitution between c^N and c^T . This parameter is important for the impact of inflation. EKMS show that with $\sigma = 0.5$, the model reproduces well the response of inflation to shocks. This value is in line with estimates in Ostry and Reinhart, 1992. The value of ρ , which determines the elasticity of substitution between y^N and y^T in production, is set to $\rho = 1.5$. Hence, F is convex; i.e., the production possibilities frontier is concave.

Terms-of-trade shocks follow

$$\ln(p_{t+1}^T) = \rho_p \ln(p_t^T) + \varepsilon_{t+1},$$

where $\varepsilon \sim N(0, \sigma_p^2)$. We set $\rho_p = 0.8803$ and $\sigma_p = 0.0756$ as estimated in EKMS. These terms-of-trade shocks will be the first out of three external shocks that we consider in the next section.

3.3 Endogenous Parameters

To determine the value of the remaining parameters, we target averages of macroeconomic variables for Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Uruguay for 1991–2018.¹ Although all the parameters are jointly calibrated, there is a close connection between some parameters and targets. The steady-state value of labor productivity A is normalized so that real GDP is 1 in steady state. The discount factor β allows the model to reproduce the target inflation rate of 3.8 percent. The transfer level γ helps match the ratio of transfers to GDP, which in the data averages 11.7 percent. The weight of leisure in utility, α^H , can be picked so that the model reproduces the long-run average for the employment-to-population ratio, 0.59. The weight of the

1. The corresponding expressions for each target are presented in Appendix Appendix 1.

Table 1
Exogenous Parameters

Parameter	Description	Value	Basis
r	Risk-free rate	0.03	Long-run average
φ	Curvature of leisure	1.50	Frisch elasticity
δ	Reentry probability	0.17	Exclusion duration
α^T	Preference share for c^T	1.00	Normalization
σ	Curvature of $u(c^N, c^T)$	0.50	See EKMS
ρ	Elasticity of substitution between γ^N and γ^T	1.50	See EKMS
ρ_p	Persistence of p^T	0.88	See EKMS
σ_p	Standard deviation of shocks to p^T	0.076	See EKMS

Table 2
Calibration Parameters and Targets

Parameter	Value	Statistic	Target	
			Data	Model
A	1.4575	Real GDP	1.000	0.995
β	0.8675	Inflation, %	3.800	4.210
γ	0.1082	Transfers/GDP	0.117	0.118
α^N	2.6888	Exports/GDP	0.209	0.208
α^H	0.9265	Employment/Population	0.587	0.586
α^G	0.4240	Gov. Purchases/GDP	0.133	0.133
B^d	0.149	Debt/GDP	0.185	0.172
ω_1	0.059	Haircut, Share of Debt	0.305	0.213
ω_2	0.656	Semi-Elasticity Spreads	-0.054	-0.053
κ	0.0235	Default, %	2.500	2.658

public good in utility, α^G , is helpful to reproduce government purchases over GDP of 13.3 percent. Similarly, the weight of nontradable consumption in utility, α^N , allows the model to reproduce the ratio of exports to GDP, which is 21 percent in the data. The next section considers unanticipated shocks to both γ and α^G as the second and third sources of external shocks.

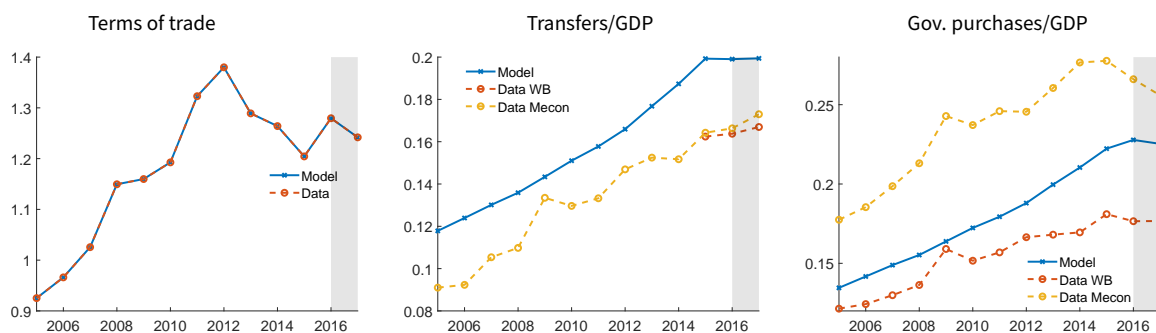
The parameters determining the cost and benefits of defaults, ω_1 , ω_2 , and B^d , are crucial in determining the implied haircut obtained by the country in default, the external debt-to-GDP ratio, and the semi-elasticity of spreads to terms-of-trade shocks. In addition, random additive shocks to utility influence the decision to repay or default; see EKMS. The scale parameter's value of this distribution, κ , helps reproduce a probability of sovereign default of 2.5 percent annually.

4. EXTERNAL SHOCKS VERSUS DOMESTIC POLICIES: ARGENTINA 2005–2017

One of the classic debates in explaining outcomes in emerging countries concerns the role of external factors and government policy. In Latin America, there is a long tradition connecting economic performance with the evolution of commodity prices. In recent work, Drechsel and Tenreiro (2017) and Fernández, González, and Rodríguez (2018) find that the contribution of commodity price shocks to output fluctuations is close to 40 percent. Poor economic performance is also attributed to government policy, e.g., high fiscal deficits and inflation. As mentioned above, Kehoe, Nicolini, and Sargent (2020) take this view and argue that economic crises in Latin America are mainly driven by inappropriate monetary and fiscal policies.

This section sheds light on this debate by studying the case of Argentina, from 2005 to 2017, through the lens of our model. During this period, Argentina fits the profile of a commodity-exporting emerging economy with rising fiscal deficit and inflation. The country experienced favorable terms of trade (good luck) due to a global boom in commodity prices. At the same time, government spending grew considerably and inflation rose significantly. Our exercise consists of simulating the Argentine experience and running counterfactuals to understand the role of external factors (favorable terms of trade) and domestic policy (increased government expenditure coupled with accommodative monetary policy).

Figure 1
Exogenous Changes



NOTE: The shaded areas correspond to the period in which Argentina had access to credit markets. “WB” is the World Bank, and “Mecon” is the Ministry of Economics in Argentina. For terms of trade, we report the data of the World Bank. Appendix 2 provides more details on the data sources.

4.1 Calibrating the Driving Forces

After the default of 2001, Argentina only had a limited number of debt issuances until 2016. To capture this period, we assume that between 2005 and 2015, the country was excluded from international credit markets but was no longer suffering a total factor productivity (TFP) penalty for being in the default state. The assumption of exclusion is evaluated below in a counterfactual exercise. The assumption of no TFP cost is motivated by two facts: (i) the period of analysis starts toward the end of the expected exclusion period, and (ii) there was no output boom when Argentina fully reentered credit markets in 2016.²

Except for the changes outlined above, we use the calibration from Section 3, which, as detailed, targets the average of several Latin American countries for 1991–2017. We use this economy as a benchmark and subject it to the changes in terms of trade and government spending experienced by Argentina from 2005 onward.

The terms of trade are expected to evolve as described in the previous section, and thus the simulation follows a particular realization path, as observed in the data. The initial value for the terms of trade are set at $p^T = 0.913$, which, in the data, matches the value in 2005 relative to the average between 1991 and 2017.³ The increase in government expenditure is modeled as a series of unexpected, permanent shocks. Since the actual levels in Argentina do not exactly match our calibration, we instead target the changes in government transfers and purchases. Specifically, we model a series of unexpected and permanent increases in two model parameters. First, we increase the transfer γ to match the increase in transfers to GDP in the data (middle panel). We then raise the multiplicative parameter in the government good’s utility function, α_G , to match the increase in government purchases to GDP (i.e., $p^N g/GDP$; see right panel).⁴

Figure 1 shows the evolution of the exogenous driving forces of the Argentine experience. The blue solid lines show the outcomes from the model simulation, while the other lines represent data according to different sources, as appropriate. The left panel shows the evolution of the terms of trade, and the other two panels show the increase in transfers and purchases, both in terms of GDP.

We compare the evolution of key macro variables in the model to those in the data to show that the simulation captures the Argentine experience reasonably well. Figure 2 presents the evolution of six macroeconomic variables.⁵ The top panel shows that the tax-revenue-to-GDP ratio and inflation increased significantly to finance government expansion while debt grew once the country reentered credit markets. The bottom left panel shows that the currency depreciation rate also increased during this period.⁶ The other two bottom panels show that the paths for real GDP and GDP measured in dollars match the data well. Overall, these findings suggest that although other things occurred in Argentina during this period, the driving forces we model capture a significant share of the macroeconomic performance.

2. Note that we maintain the assumption that the country would experience a TFP penalty if it were to default in the future.

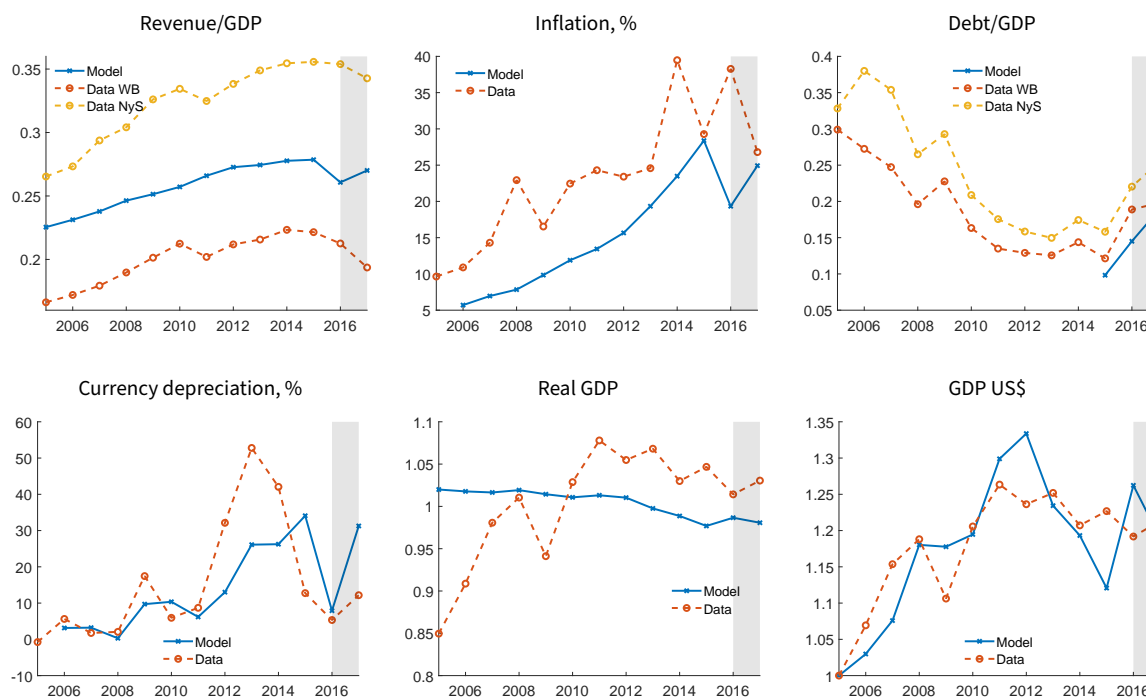
3. We also computed the exercises for different initial values of p^T . Our results do not change fundamentally if we instead started at the average value for the terms of trade.

4. Specifically, we assume that between 2005 and 2015, γ and α_G grow at 5.14 percent and 6.40 percent per year, respectively.

5. The exercise starts in 2005, so the model predictions for inflation and currency depreciation start in 2006 as both of these variables depend on the previous year’s Consumer Price Index (CPI) and exchange rate, respectively.

6. During part of this period, Argentina had multiple nominal exchange rates. The figure shows the devaluation in the black market rate (as reported in recent updates of the data set constructed in Ferreres, 2005).

Figure 2
Comparison of Key Macro Variables—Model versus Argentina



NOTE: The shaded areas correspond to the period in which Argentina had access to credit markets. “WB” is the World Bank, and “NyS” corresponds to recent updates of the data set constructed by Ferreres, 2005. Data for inflation are from “NyS.” For depreciation, exchange corresponds to the black market as reported in “NyS.” Real GDP is from the World Bank, and GDP in US\$ is from “NyS.” Appendix 2 provides more details on the data sources.

4.2 The Role of External Factors and Domestic Policy

Having shown that the model fits the evolution of macroeconomic variables in Argentina reasonably well, we proceed to perform some counterfactual exercises. First, to isolate their relative contribution, we run our simulations assuming that only one of the driving forces is present at a time. Figure 3 shows the evolution of several macroeconomic variables under alternative scenarios. First, we consider the case with only shocks to the terms of trade, and we keep the values of α^G and γ at the original level. Second, we consider only the shocks to fiscal expansion and keep the terms of trade constant at the original level. Third, we also show the benchmark with all shocks for comparison.

The improvement in the terms of trade does not contribute to the increase in government purchases, though it has a clear effect on revenue. Similarly, more favorable terms of trade do not explain the increase in inflation and depreciation, but they do contribute to short-term fluctuations in these variables. We can also see that the rise in the terms of trade has a positive effect on real GDP.

On the other hand, the expansion of government spending explains the rise in inflation and currency depreciation and, in part, the increase in tax revenue. The permanent nature of these changes implies that the impact on debt is minor. Importantly, the increase in distortions associated with larger government expenditure (purchases and transfers) proves a significant drag to the real economy, pushing real GDP down.

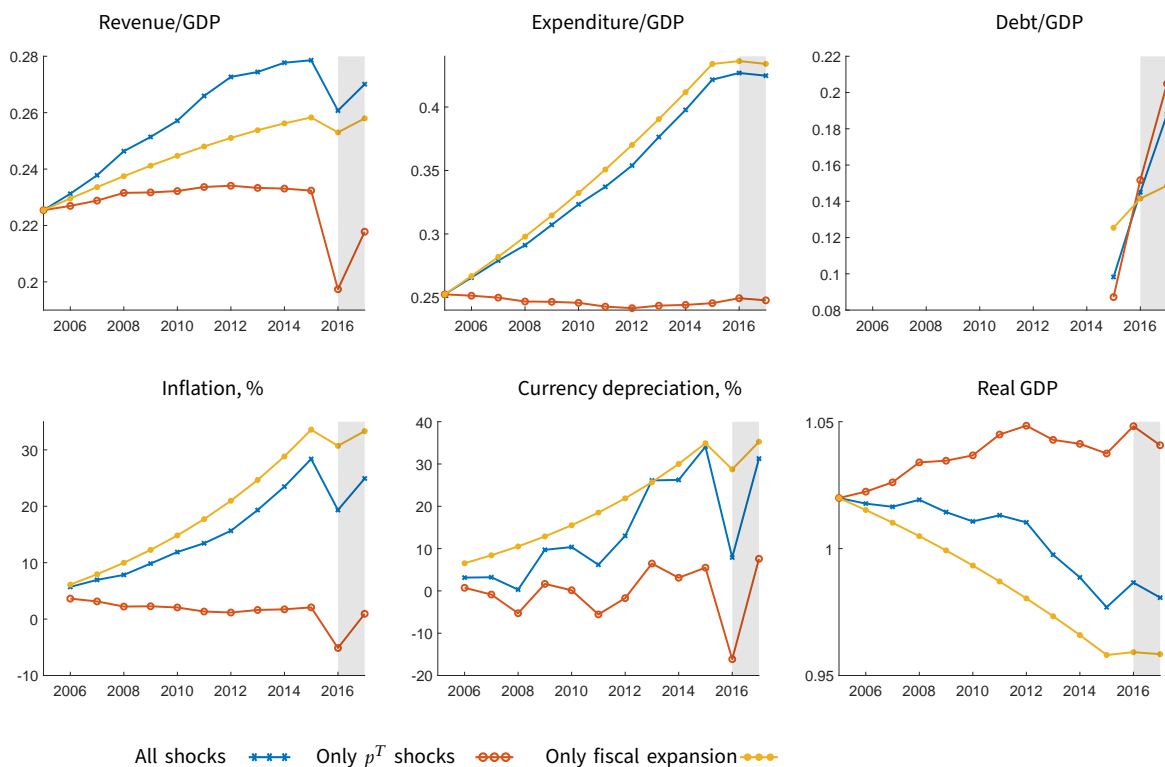
Our simulations suggest that had there not been a dramatic expansion of the government, Argentina would have reaped the benefits of favorable terms of trade: inflation and currency depreciation would have been low and output high. However, the rapid expansion of foreign currency debt after the country regained access to credit markets appears entirely attributable to international circumstances rather than to the profligacy of its government.

4.3 The Role of Monetary Policy

A natural follow-up question is what would have happened if Argentina adopted a more disciplined monetary policy. In a follow-up article, we study the role and welfare effects of fiscal and monetary rules in emerging markets—see Espino et al. (2023). Here, we study the effect of a monetary rule in a specific context.

Figure 4 shows the effects of assuming a constant money growth rate throughout this period, a type of

Figure 3
Evolution of Key Macro Variables in Alternative Scenarios



policy that was eventually adopted in late 2018 to curb inflation.⁷ Relative to our benchmark, this monetary policy would have kept inflation low and stable (except for the year in which the country reentered international credit markets). In addition, currency depreciation would have mostly been explained by the variation in the terms of trade. Note that seigniorage (defined as μ over GDP) is about 3 percent in 2005 and would have decreased with a constant μ . However, in the benchmark simulation with the fiscal expansion, seigniorage increases to about 14 in 2014. However, implementing a constant money growth rate would have required a significant increase in taxation to finance the expansion of government. This suboptimal choice of distortions would have resulted in a lower real GDP.

To better understand the countercyclical role of policy in offsetting terms-of-trade shocks, we now focus on 2013, when the terms of trade fell by 6.6 percent after reaching their peak in 2012. Relative to the benchmark, the impact of this event when adopting a constant monetary policy is smaller on inflation (0.8 percentage points versus 3.7 percentage points) and currency depreciation (8.6 percentage points versus 13.1 percentage points). However, taxes should have increased more (2.3 percentage points versus 0.2 percentage points), so the decline in real GDP is even more significant (−1.7 percent versus −1.3 percent).

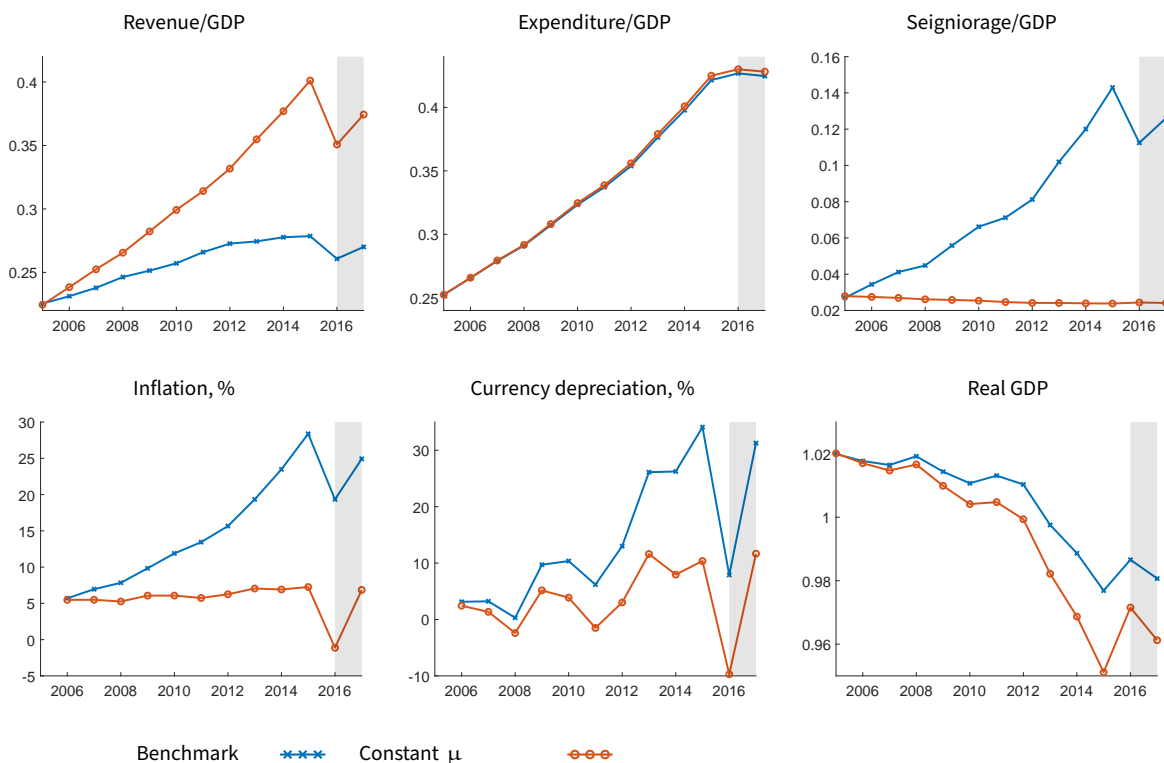
These results provide a cautionary tale for policy recommendation: implementing a conservative monetary policy in the face of an expanding government may succeed in keeping inflation under control but without addressing the underlying fiscal imbalance, and so it may also lead to a deeper economic recession. In addition, a strict monetary policy hinders the government's ability to handle external shocks. In our counterfactual exercise, we have allowed revenue to adjust as necessary, so the cost is borne by the real economy in the form of lower real output due to higher distortions. One could also imagine a scenario in which taxes cannot be raised sufficiently due to political considerations. If the central bank were not to relent under these circumstances, this scenario might eventually lead to a debt crisis.

4.4 The Role of Exclusion from International Credit Markets

We have assumed that the country was excluded from international credit markets from 2005 to 2015 since, in reality, access to external credit was minimal during this period. We now study the role of this exclusion by simulating an economy that can issue external debt throughout the entire period. The red lines in Figure

7. In our simulation, we set the money growth rate equal to the average rate in the benchmark economy, $\mu = 0.0418$.

Figure 4
Evolution of Key Macro Variables When μ Is Constant

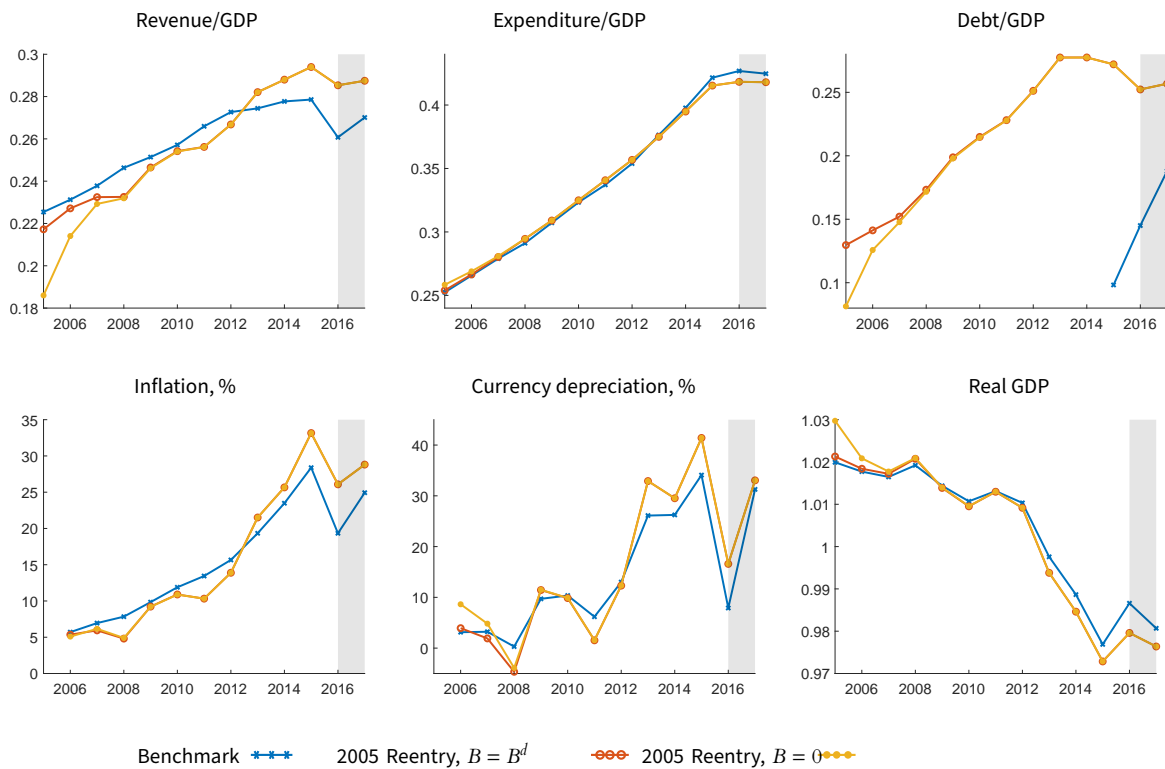


5 follow the economy with access to international credit markets, starting off in 2005 with a debt level of B^d , as highlighted by the evolution of debt in the right top panel. The yellow lines also assume that the economy can issue debt but with a reentry level of debt equal to zero, i.e., with a haircut after default of 100 percent of the debt.

Overall, the impact of having earlier access to international credit markets is not as significant as one might have expected. Having access to external credit allows the government to borrow from abroad and thus impose lower distortions (taxes and inflation) early on. These lower early policy distortions come at the cost of higher later distortions, as debt builds up and its service costs increase. As a consequence, at the end of the period of analysis, real GDP is slightly lower with early access to international credit than in the benchmark economy. The value of the debt haircut (i.e., the level of debt at reentry) only affects the transition in the first two years. With a higher haircut (lower initial debt), the government implements lower taxes, lower inflation, and slightly higher expenditure. These effects are only present in 2006 and 2007. Starting in 2008, the two economies with different haircuts experience the same economic performance.

Again, we find it instructive to focus on the reaction of policy and real variables in 2013, when the terms of trade dropped sharply after reaching their peak. A priori, one would think that having access to external debt would have enabled the government to better smooth the shock. However, for the case when the government has access to international credit markets as of 2005, the country reaches 2012 with a high debt-to-GDP ratio—recall that, in the benchmark, the government is still not allowed to issue external debt. Relative to the benchmark, when the government has access to international credit, there is a larger reaction of inflation (7.6 percentage points versus 3.7 percentage points) and currency depreciation (20.6 percentage points versus 13.1 percentage points), which leads to a larger contraction in real GDP (−1.5 percent versus −1.3 percent). The higher debt burden in the alternative scenario results in the need for higher policy distortions, increasing both taxes and money financing. This implies a higher output loss, more inflation, and a more pronounced nominal depreciation. Hence, the moral is that access to international credit markets without dealing with the underlying fiscal imbalance ends up limiting the capacity of the country to absorb the fall in the terms of trade and implies a more extreme negative response of the economy.

Figure 5
Evolution of Key Macro Variables with Alternative Exclusion and Reentry



5. CONCLUDING REMARKS

We use the framework of EKMS to study the experience of Argentina in 2005–2017, focusing on the role of external shocks and domestic policies in shaping economic outcomes. During that period, Argentina experienced exceptionally favorable terms of trade but also embarked on a significant expansion of its government. According to our findings, the rise in spending accounted for the large increase in the size of the government, the steady increase in inflation, and the poor performance of output growth.

APPENDIX 1. DEFINITION OF MACROECONOMIC AGGREGATES

- Nominal GDP (in pesos, normalized by the money stock):

$$Y_t = e_t p_t^T \gamma_t^T + p_t^N \gamma_t^N.$$

- GDP in foreign currency (USD):

$$Y_t^{USD} = p_t^T \gamma_t^T + \frac{1}{e_t} p_t^N \gamma_t^N.$$

- GDP deflator (in pesos, normalized by the money stock):

$$P_t^Y = \left(\frac{e p^T \gamma^T}{Y} \right) e_t p_t^T + \left(\frac{p^N \gamma^N}{Y} \right) p_t^N.$$

- Real GDP:

$$Y_t^R = \frac{Y_t}{P_t^Y}.$$

- Consumption expenditure (in pesos, normalized by the money stock):

$$C_t = e_t c_t^T + p_t^N c_t^N.$$

- Consumption price index (in pesos, normalized by the money stock):

$$P_t^C = \left(\frac{e c^T}{C} \right) e_t + \left(\frac{p^N c^N}{C} \right) p_t^N.$$

- Inflation, measured as the change in the consumption price index:

$$\pi_t = \frac{P_t^C}{P_{t-1}^C} (1 + \mu_{t-1}) - 1.$$

- Currency depreciation:

$$\Delta_t = \frac{e_t}{e_{t-1}} (1 + \mu_{t-1}) - 1.$$

Note that inflation and currency depreciation are corrected by the money growth rate since prices are normalized by the money stock.

APPENDIX 2. DATA SOURCES

This section lists the sources for all the variables used in the main body of the article.

Variables in Table 2:

- “Inflation” is inflation, consumer prices (annual %) from the World Bank. Indicator code FP.CPI.TOTL.ZG.
- “Transfers/GDP” is constructed as the product of two series from the World Bank. Subsidies and other transfers (percentage of expense) with indicator code GC.XPN.TRFT.ZS and expense (percentage of GDP) with indicator code GC.XPN.TOTL.GD.ZS.
- “Exports/GDP” is exports of goods and services (percentage of GDP) from the World Bank. Indicator code NE.EXP.GNFS.ZS.
- “Employment/Population” is the employment-to-population ratio, 15+, total (percentage) (modeled International Labour Organization estimate). Indicator code SLEMP.TOTL.SP.ZS.
- “Gov. Purchases/GDP” is general government final consumption expenditure (percentage of GDP) from the World Bank. Indicator code NE.CON.GOV.T.ZS.
- “Debt/GDP” is public external debt (percentage of GDP) computed using the ratio of the following two variables from the World Bank: external debt stocks and public and publicly guaranteed (PPG) (debt outstanding and dispersed, current US\$) with indicator code DT.DOD.DPPG.CD and GDP (current US\$) with indicator code NY.GDP.MKTP.CD.
- “Haircut, Share of Debt” is the median “SZ haircut, HSZ” in Table 2 of Dvorkin et al., 2021.

- “Default” is obtained from Tomz and Wright, 2013. They construct a database of 176 sovereign entities spanning 1820 to 2012. The frequency of default is sensitive to the sample being analyzed. They mention that their findings are “similar to the 2% default probability that is a target for many calibrated versions of the standard model,” which is the number we use as well. The unconditional probability of a country with positive debt (a borrower) defaulting on debts owed to commercial creditors is 1.7 percentage per year. Nevertheless, this probability is higher in developing countries. Note also in Figure 2 of Tomz and Wright, 2013 that in a typical year, there are no defaults or there is one country in default. We considered this fact when calibrating a significantly lower default rate in the model with only ε shocks.

The data sources for Figures 1 and 2 that came from the World Bank were already described. The other sources are the following:

- Transfers/GDP labeled “Mecon” is taken from the Ministry of Economics of Argentina information about “Gasto Publico Consolidado 1980–2017 por finalidad” as a share of GDP, and it corresponds to the sum of “II.2.2. Obras sociales - Atención de la salud,” “II.2.3. INSSJyP - Atención de la salud,” “II.6. Previsión social,” and “II.7. Trabajo.” The data can be found in <https://www.argentina.gob.ar/economia/politicaeconomica/macroeconomica/gastopublicoconsolidado>.
- Gov. Purchases/GDP labeled “Mecon” is taken from the Ministry of Economics of Argentina information about “Gasto Publico Consolidado 1980–2017 por finalidad” as a share of GDP, and it corresponds to the “Gasto Publico sin Servicios de la Deuda Publica (IV)” minus transfers as defined above.
- “Revenue/GDP” labeled as “NyS” corresponds to data from the “Fundacion Norte y Sur,” file C7.2, tab “Ingresos, Gastos y Resultado del Sector Público Argentino,” column “Ingresos totales % PIB.” The data can be found in <https://dossiglos.fundacionnorveysur.org.ar/series>.
- “Debt/GDP” labeled as “NyS” corresponds to data from the “Fundacion Norte y Sur,” file C7.2, tab “Deuda publica nacional interna y externa consolidada,” column “Deuda Publica Externa.”
- “Currency Depreciation % Data” corresponds to data from the “Fundacion Norte y Sur,” file C8.2, tab “Tipo de Cambio,” column “Dolar Libre.”

REFERENCES

- Arellano, Cristina. 2008. Default risk and income fluctuations in emerging economies. *American Economic Review* 98(3):690–712.
- Cruces, Juan J., and Christoph Trebesch. 2013. Sovereign Defaults: The Price of Haircuts. *American Economic Journal: Macroeconomics* 5, no. 3 (July): 85–117.
- Das, Udaibir S, Michael G Papaioannou, and Christoph Trebesch. 2012. *Sovereign debt restructurings 1950–2010: literature survey, data, and stylized facts*. Working Paper 12/203. IMF.
- Drechsel, Thomas, and Silvana Tenreyro. 2017. *Commodity booms and busts in emerging economies*. NBER Working Paper 23716. August.
- Dvorkin, Maximiliano, Juan M Sánchez, Horacio Sapriza, and Emircan Yurdagul. 2021. Sovereign debt restructurings. *American Economic Journal: Macroeconomics* 13 (2).
- Espino, Emilio, Julian Kozlowski, Fernando M Martin, and Juan M Sanchez. 2022. Domestic policies and sovereign default. *FRB St. Louis Working Paper*, nos. 2020–17.
- Espino, Emilio, Julian Kozlowski, Fernando M Martin, and Juan M Sánchez. 2023. Policy rules and large crises in emerging markets. *FRB St. Louis Working Paper*, nos. 2022–18.
- Fernández, Andrés, Andrés González, and Diego Rodríguez. 2018. Sharing a ride on the commodities roller coaster: Common factors in business cycles of emerging economies. *Journal of International Economics* 111 (C): 99–121.
- Fernández, Andrés, Stephanie Schmitt-Grohé, and Martín Uribe. 2017. World shocks, world prices, and business cycles: an empirical investigation. *Journal of International Economics* 108 (Supplement 1): S2–s14.
- Ferreres, Orlando J. 2005. *Dos siglos de economía argentina, 1810–2004: historia argentina en cifras*. Editorial El Ateneo.
- Kehoe, Timothy J, Juan Pablo Nicolini, and Thomas J Sargent. 2020. A framework for studying the monetary and fiscal history of Latin America, 1960–2017. Federal Reserve Bank of Minneapolis.

- King, Mervyn, and David Low. 2014. *Measuring the “world” real interest rate*. NBER Working Paper 19887. February.
- Ostry, Jonathan D., and Carmen M. Reinhart. 1992. Private Saving and Terms of Trade Shocks: Evidence from Developing Countries. *IMF Staff Papers* 39, no. 3 (September): 495–517.
- Tomz, Michael, and Mark LJ Wright. 2013. Empirical research on sovereign debt and default. *Annual Review of Economics* 5 (1): 247–272.
- Uribe, Martin, and Stephanie Schmitt-Grohé. 2017. *Open economy macroeconomics*. Princeton, New Jersey: Princeton University Press.

Tornado Cash and Blockchain Privacy: A Primer for Economists and Policymakers

Matthias Nadler and Fabian Schär

Abstract

This article explores non-custodial crypto asset mixers such as Tornado Cash. We analyze what types of mixers exist and how they work. We discuss opportunities and risks and offer an approach, based on voluntary disclosure, that would allow financial market regulators to combat money laundering and illicit activities, while allowing honest users to interact with privacy-enhancing protocols. We explain how crypto asset mixers play an important role on public blockchains and that privacy may be difficult to attain without them.

JEL codes: B27, D53, G18

Federal Reserve Bank of St. Louis *Review*, Second Quarter 2023, 105(2), pp. 122-36.

<https://doi.org/10.20955/r.105.122-136>

1 INTRODUCTION

It is difficult to retain privacy on a public blockchain. In contrast to popular belief, permissionless blockchains are completely transparent. All confirmed transactions are publicly observable and stored as part of the blockchain's history. The users' identities are only protected through the use of addresses that act as pseudonyms. This setup allows public blockchains to operate without any intermediaries and creates a system where everyone can mathematically verify the legitimacy and integrity of transactions as well as the current state of the ledger; but the setup raises severe privacy concerns.

If someone obtains information that allows them to link a blockchain address to an entity, they may effectively observe that entity's entire transaction history and associated activity. Even if the entity uses multiple addresses, any link between these addresses may expose the fact that they belong to the same person. Moreover, the immutable and public nature of the data creates a setting where the data accrues over time and will always be available for analysis. The algorithms and tools to analyze the data will become more sophisticated, off-chain data more abundant, and computational constraints less relevant.

Fabian Schär is a professor for distributed ledger technologies and fintech at the University of Basel and the managing director of the Center for Innovative Finance at the Faculty of Business and Economics, University of Basel. Matthias Nadler is a PhD candidate at the Faculty of Business and Economics, University of Basel. The authors thank Tobias Bitterli, George Fortier, Andrea Glarner, Mitchell Goldberg, Emma Littlejohn, Remo Nyffenegger, Katrin Schuler, Dario Thürkauf, and the editors and referees of the *Review*.

© 2023, Federal Reserve Bank of St. Louis. The views expressed in this article are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Articles may be reprinted, reproduced, published, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. Abstracts, synopses, and other derivative works may be made only with prior written permission of the Federal Reserve Bank of St. Louis.

To preserve some privacy, many users rely on so-called crypto asset mixers (sometimes also referred to as tumblers or privacy-enhancing protocols). Other ideas for achieving (partial) privacy on public blockchains exist,¹ but crypto asset mixers are currently the most widely used approach. Simply put, the goal of a crypto asset mixer is as follows: Various entities² deposit the same amount of a specific crypto asset to a mixer address. The mixer acts as a pool. Anyone who has contributed to the pool may then generate a new address and withdraw their funds without revealing the link between the depositor and withdrawal addresses. To be precise: Third parties can still observe the addresses that have deposited to and withdrawn from the pool, but given a large enough anonymity set (see Section 4.2), those third parties cannot link a *specific* depositor address to a *specific* withdrawal address. Thus, crypto asset mixers break the visible link between transactions.

To provide a simple example, let us assume that Alice has sent a crypto asset to Bob. Bob now knows Alice's public address and may potentially observe her account for other activity. To hide her future activity from Bob, Alice could deposit funds to a crypto asset mixer. In this mixer, the funds are pooled with deposits from Carl and Dave who have also deposited funds in equal denominations. When Alice later uses a different address to withdraw from the pool, Bob will not be able to tell whether the new account belongs to Alice, Carl, or Dave.

Given the high degree of transparency on public ledgers, there certainly is a legitimate privacy use case for crypto asset mixers. However, there is also strong evidence that crypto asset mixers are being used for money laundering and to hide traces of illicit activities. On various occasions, funds resulting from hacks have been deposited to Tornado Cash. Some of these hacks were allegedly conducted by the North Korean hacker group *Lazarus*. Estimates by crypto analytics firms suggest that almost 30% of the funds deposited to Tornado Cash have originated from illicit activities.³ These circumstances have led to a lot of regulatory scrutiny.

On August 8, 2022, the U.S. Treasury's Office of Foreign Asset Control (OFAC) placed the Tornado Cash smart contracts on the Specially Designated Nationals and Blocked Persons (SDN) sanctions list, effectively making it illegal for U.S. citizens to interact with the Tornado Cash protocol. The OFAC has added custodial addresses (including custodial mixing services) to the SDN before, but this Tornado Cash sanction is the first time a non-custodial protocol has been targeted.

The goal of this article is to provide an interdisciplinary introduction to non-custodial crypto asset mixers, to create a foundation for economists and policymakers, and to enable further research at the intersection of privacy and illicit activity. We use Tornado Cash as an example to show how non-custodial crypto asset mixers work. We collect and present data that may be useful for researchers and policymakers, point toward new regulatory challenges, and present potential solutions to some of the problems.

Crypto assets in general is a highly interdisciplinary topic. The related topic of non-custodial crypto asset mixers is especially complex, and it is not possible to adequately discuss its challenges and opportunities without some technical background. Since this article is targeted mainly at economists and policymakers, we introduce some of the technical core concepts used in non-custodial crypto asset mixers in the next section. This allows readers without a technical background to understand how the protocol works and follow the analysis and discussion more easily.

1. For example non-interactive stealth addresses, see <https://github.com/ethereum/EIPs/blob/master/EIPS/eip-5564.md>

2. Note that it is also possible for the same entity to make several deposits. Either through the same or multiple depositor addresses.

3. See <https://blog.chainalysis.com/reports/tornado-cash-sanctions-challenges/>

2 BACKGROUND

Crypto asset mixers can be implemented at various levels of technological sophistication. The simplest version is a custodial model, where a centralized service provider operates the mixing service. Users send their funds to the mixing service's public deposit address and specify a recipient address over a private channel. While this can work in principle, custodial mixers are entirely trust-based. First, users must trust the service provider to fulfill their obligation and transfer the funds to the deposit addresses. The service provider is in full control of the assets and could invest, lend, or potentially steal them. Second, since the centralized entity knows the link between the deposit and recipient address, the user's privacy depends on the service provider's ability and willingness to irrevocably dispose of the identifying data after the mixing operation has concluded.

Non-custodial crypto asset mixers do not require trust. Instead, they rely on cryptographic schemes that allow anyone to prove and independently verify the validity of a withdrawal without disclosing the link to a specific deposit. Moreover, the user does not have to share the identifying information with anyone and there is no liquidity risk, since the funds are locked and cannot be used in any other way. As such, non-custodial mixers can be created as an immutable and independent infrastructure, where no centralized entity can unilaterally control, alter, or delete the information.

This distinction is in line with FinCEN's guidance document⁴ that differentiates between anonymizing service providers (money transmitters) and anonymizing software providers (not money transmitters). While custodial mixing services operate as money service providers and constitute a legal entity that can be regulated, the situation is less clear in the context of non-custodial mixing protocols. The FinCEN guidelines suggest that they do not fall within the domain of a money transmitter.

The basic challenge with non-custodial crypto asset mixers is that there are two conflicting goals. On the one hand, the protocol's purpose is to break the link between the depositor address and the recipient address. As such, it cannot store information that would allow anyone to see how deposits and withdrawals are linked. On the other hand, it must ensure that (i) withdrawals can be initiated only by entities who have previously deposited funds and (ii) any given deposit can be withdrawn only once.

In what follows we briefly lay the foundations and discuss the individual building blocks that are needed to allow for public validation of these two conditions without violating privacy. Readers who have a technical background and are familiar with smart contracts, hash functions, Merkle trees, and zkSNARKs can go directly to Section 3.

2.1 Smart Contracts

Most non-custodial crypto asset mixers (including Tornado Cash) are based on smart contracts. A smart contract is a script that is immutably stored on the blockchain and runs as part of the blockchain's consensus protocol.

The term smart contract was proposed by Szabo (1994, 1997). The first smart contract blockchain was proposed by Buterin (2014) and formalized by Wood (2015).

Smart contracts are accounts with their own distinct address. Instead of being controlled by a private key, smart contracts are controlled by code. By default, the contract logic cannot be changed after deployment. Any asset that is sent to the smart contract will remain in control of this smart contract until a condition in its code is met that will transfer the assets to a new address.

A smart contract has two main components: *functions* (or methods) and *state variables*.

Functions can be interpreted as the smart contract's action set. Any interaction with a smart contract is initiated by a transaction that specifies a function call. If Alice wants to interact with the smart contract, she issues a transaction. She sets the *recipient* address to the smart contract's address and adds

4. See FIN-2019-G001, <https://www.fincen.gov/sites/default/files/2019-05/FinCEN%20Guidance%20CVC%20FINAL%20508.pdf>

information on what function she wants to call. If the function has arguments (parameters), she chooses these values and adds them to the transaction. As a simple example, imagine a smart contract that allows Alice to store a number. When she calls the `store()` function, she is expected to add a number of her choice as a function argument. When the transaction is confirmed, the smart contract function will be executed and the smart contract state updated. The update is reflected in the state variables.

State variables can be interpreted as the smart contract's long-term memory. Any information that must be stored by the smart contract will be assigned to a state variable. The values may change in line with the specific rules of the smart contract when a function is being executed. In our simple example, the value Alice chose as an argument for her function call would be stored in the contract state.

For a more detailed introduction to smart contracts and their applications in financial markets, see Schär (2021).

2.2 Hash Functions

Hash functions map an input of quasi-arbitrary length to a fixed-length output. Essentially, the output is a deterministic digest of the input data. More formally, let us define $H(x) = h$, where $H()$ is the hash function, x the input and h the resulting output, usually referred to as *hash value*. Hash functions have two main applications: checksums and cryptographic fingerprints.

Checksums are used to decrease the probability of undetected typos. Prominent examples include checksum applications in credit card and bank account numbers. To provide a simple example, let us assume that x is a basic account number without a checksum. Using x as an input for $H(x)$ would yield checksum h . The actual account number including the checksum can then be represented as $I = h||x$, where the two pipes represent a simple concatenation. A typo in I would likely create incompatible x and h values and allow anyone to detect the typo with probability $1 - \frac{1}{e}$, where e represents the size of the hash function's uniformly distributed mapping set. In other words, a two-digit checksum with $h \in \{0, \dots, 99\}$ means that 99% of all typos can be detected through the validation of $h == H(x)$.

Cryptographic fingerprints are usually used to ensure inclusion and integrity of information or to set up schemes, in which the knowledge of x serves as a secret and h is stored as a reference for validation purposes. They therefore add the additional requirement of collision resistance. Collision resistance in the context of hash functions means that, given a function $H(x)$, it is infeasible to find more than one x for a given output h . This requires a very large e . Most cryptographic hash functions use $e \geq 2^{160}$. Moreover, the function must be one-way, referring to the property that it must be infeasible to invert the computation. In other words, one can verify that h is the digest of a given x but one cannot derive x from h .

A simple introduction to the application of cryptographic hash functions in the context of Bitcoin can be found in Berentsen and Schär (2018).

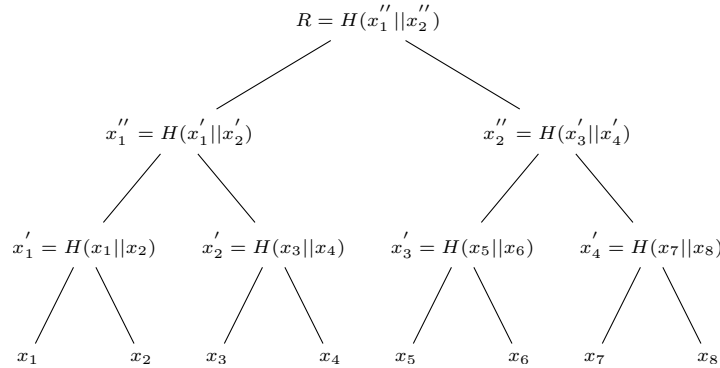
2.3 Merkle Trees

Let us assume that \mathbf{x} is a vector of length N , with $\mathbf{x} = (x_1, \dots, x_N)$. One could easily concatenate the elements of the vector and use $H(x_1||x_2||\dots||x_{N-1}||x_N) = h$ to compute a hash value that acts as a fingerprint for \mathbf{x} . The problem with this approach is that h can be used to prove $x_i \in \mathbf{x}$ only if the prover has knowledge of the entire input vector \mathbf{x} . In other words, using the hash value to prove that some element x_i is part of the input vector \mathbf{x} requires a large amount of input data and is unnecessarily inefficient. For these reasons, hash-based integrity proofs for multiple values usually rely on a data structure referred to as a *Merkle tree*.

Merkle trees hash the elements of an initial input vector pairwise.⁵ Any x_i with an uneven index is hashed with the next element of the vector. In case of an uneven N , an element with value zero is

5. The elements of the initial input vector are sometimes referred to as *leaves*.

Figure 1
Simple Example of a Merkle Tree with Eight Leaves



NOTE: In this simple Merkle tree, the example input vector (x_1, \dots, x_8) is hashed recursively and pairwise until a single hash, the root, remains.

appended. The resulting hash values are stored in a new vector \mathbf{x}' . The process is repeated with \mathbf{x}' as the new input vector until the resulting output vector is of length 1. This value is referred to as the *Merkle root* and denoted by R . The number of rounds needed to arrive at the Merkle root is referred to as the height of the Merkle tree, with $\log_2(N)$. In other words, a Merkle tree with an initial input vector of length 8 has height 3. This example is visualized in Figure 1.

To prove that x_i is part of \mathbf{x} for a given R , one simply needs the values for x_i and $\log_2(N)$ nodes along the path of the corresponding Merkle proof. Consider the following example: To construct a proof that x_5 is part of \mathbf{x} for a given R , the values for x_6 , x'_4 , and x''_1 would suffice. As such, one can construct very efficient inclusion proofs, particularly for initial input vectors with a large N .

2.4 zkSNARKs

zkSNARK stands for *zero knowledge, succinct, non-interactive argument of knowledge*. Let us discuss these properties one by one.

Argument of Knowledge: Intuitively this means that a person can construct a proof that demonstrates the knowledge of a secret value. The argument system is said to be *complete* if there are no false negatives and *sound* if the probability for false positives is negligible.

Zero Knowledge: The proof is said to be zero knowledge if it does not reveal the secret value or any other information besides the proof that a statement is true. In the context of Tornado Cash, Alice will be able to construct a proof that she has previously deposited to the Tornado Cash contract without having to reveal the specific deposit transaction.

Non-Interactive: The proof does not require any direct interaction between prover and verifier. In other words, a single message from the prover to the verifier is sufficient and the same proof can be used to convince any number of verifiers. This contrasts with interactive proofs, where each verifier sends multiple messages with cryptographic challenges to the prover. In a blockchain context, interactive argument systems are not feasible.

Succinct: The proof is referred to as succinct if it can be efficiently verified with respect to data size and verification runtime. Both properties are important in a blockchain context, as large input or storage data as well as complex on-chain computations would be infeasible.

Although zkSNARKs are an important part of Tornado Cash, a mathematical discussion is out of scope for this article. The reader who wishes to learn more about the mathematical principles behind zkSNARKs can turn to Petkus (2019), Thaler (2022) or Berentsen et al. (2022).

What we need to know for our analysis is that SNARKs use prover and verifier functions (more precisely, arithmetic circuits) that represent the argument system and are initialized through parameters, resulting from a trusted initiation (or setup) ceremony. We will treat the circuits as black boxes and assume that they satisfy the properties mentioned above. However, what is important to understand is that SNARK-based argument systems require an initiation ceremony in which some external entropy must be provided. These data must be discarded after the initiation ceremony, as anyone in possession of them could construct fake proofs.

Tornado Cash deals with this issue through a decentralized initiation ceremony in which anyone could sequentially contribute to the setup. If at least one contributor discards their secret contribution, it becomes impossible for anyone to generate fake proofs. In total, the Tornado Cash ceremony had 1,114 participants,⁶ of which 664 remained anonymous and 450 provided their identity. Having both anonymous and identified participants is advantageous, as it mitigates collusion and blackmailing (potential problem with known actors) and sybil attacks where a single person participates with multiple anonymous accounts (potential problem with anonymous actors).

3 PROTOCOL DESCRIPTION

Tornado Cash is a smart contract-based crypto asset mixer that uses zkSNARKs to create a decentralized privacy-enhancing protocol. The code is open source and has been deployed on various blockchains, most notably Ethereum.

In this section we revisit our example from the introduction and analyze what is happening from a more technical perspective. We will use the protocol's two main functions and follow Alice as she makes a deposit and a privacy-enhancing withdrawal. The notation is mostly based on Khovratovich and Vladimirov (2019).

3.1 Deposits

Before depositing any funds, Alice chooses two random numbers, $k \in \mathbb{B}^{248}$ and $r \in \mathbb{B}^{248}$, with $\mathbb{B} = \{0,1\}$, where k is referred to as a nullifier and will later be used to prevent double spends, and r is a source of entropy. Note that both values are known only to Alice and must remain secret at all times. Alice uses a cryptographic hash function $H_1()$ to compute $C = H_1(k||r)$. C is usually referred to as a coin; however, it is easier to think of it as a cryptographic commitment that allows Alice to anonymously withdraw her funds at a later point in time, provided that she has securely stored k and r . If Alice loses access to this information, she will not be able to withdraw her funds. Similarly, if someone else learns the values for k and r , this person can steal Alice's funds.

After the local computations have concluded and Alice has properly stored her secret values, she issues a blockchain transaction, through which she calls the Tornado Cash contract's `deposit()` function. The transaction must include crypto assets in line with the pool's asset class and denomination. In other words, if Alice wants to deposit to the 1 ETH pool, she must add 1 ETH to the transaction. In addition, she includes data C , which will be used as a parameter in smart contract execution. Recall that C is a cryptographic hash value. Consequently, it represents Alice's choices of k and r through a cryptographic fingerprint, but it does not reveal the actual values of k and r .

When the transaction is executed and confirmed, the funds are locked in the Tornado Cash contract and the contract's state is updated accordingly. The contract stores a Merkle tree with height 20,⁷ where

6. See <https://tornado-cash.medium.com/the-biggest-trusted-setup-ceremony-in-the-world-3c6ab9c8fffa>

7. This leads to $2^{20} = 1,048,576$ leaves, which can be interpreted as an upper limit for the deposits in this pool.

each leaf can store a C from a deposit transaction. The C value from Alice's transaction is added to the next empty leaf and the Merkle proof values and root R are updated accordingly.⁸

Referring to our example in Figure 1, the new C value would be stored in x_i , where index i is the position of the first empty leaf in the tree.

3.2 Withdrawals

To withdraw, Alice has to pre-compute various data and issue a transaction that calls the `withdraw()` function of the Tornado Cash contract.

First, she creates a new Ethereum address A . This address will be the destination for her funds. Since it is a newly created address, there is no prior history that may reveal the link to Alice. Second, she computes a nullifier hash $\phi = H_2(k)$, where $H_2()$ is a different cryptographic hash function.

Third, she selects a recent R , which is a root that includes the C from her deposit and uses the prover circuit from the trusted setup ceremony to construct a proof P . The construction of this proof requires knowledge of k and r , as well as the leaf index i , which is the leaf position where her C is stored.

She then issues a blockchain transaction that calls the `withdraw()` function of the Tornado Cash contract, sending along A , R , P , and ϕ as arguments for the function.

As part of transaction execution, the contract verifies the following conditions:

1. Using the verifier circuit from the trusted setup ceremony, P must be a valid proof for the provided parameters A , R , and ϕ .
2. The presented nullifier hash ϕ has not been previously revealed as part of another withdraw transaction.

If both conditions can be verified successfully, the contract sends the corresponding value to A and adds ϕ to a list of previously revealed nullifier hashes.

Intuitively, condition 1 verifies if Alice has indeed deposited to the contract and thereby created a C . The Merkle root R is used as a summary for all C values. Using the Merkle tree structure and zkSNARK-based argument system, Alice can prove that she knows a tuple (k, r) that hashes to a C , which is part of the Merkle tree, without revealing which C she is referencing. The destination address A is included in the proof to make sure that it cannot be changed without invalidating the proof. Otherwise, anyone could use an already constructed proof, change the destination address, and try to front-run the transaction.

The second condition prevents double spends. Since the computation of the nullifier hash is also part of the prover circuit, any additional attempts to spend the same C more than once will result in a nullifier hash that has already been revealed. Similarly, setting the nullifier hash to an arbitrary value will create an invalid proof, since any $k' \neq k$ would lead to a different C value.

4 EMPIRICAL ANALYSIS

In this section we use on-chain data to give an overview of the usage and scale of Tornado Cash. First, we introduce the different asset pools and present monthly transaction counts and U.S. dollar volumes. We show the total scope of the protocol as well as its usage over time. Second, we analyze how protocol user anonymity can be quantified and how it evolved over time.

All the data in this section were gathered and verified with a personal Ethereum node.⁹ The observation horizon is from each pool's first deposit up to and including block 15,449,617, the last block in

8. The smart contract stores the last 100 values for R . The reason for this is that the withdrawal transaction must reference a specific R . If the contract allowed only for the latest R to be referenced, a dedicated attacker could front run withdrawals with deposits and thereby cause the withdrawals to fail.

9. The exact software we used is a self-hosted Erigon archive node, see <https://github.com/ledgerwatch/erigon>

Table 1
Transaction Count and Usage Statistics of Tornado Cash

Pool	Observations (No. of days)	Transactions				Deposit volume	
		Deposit	Withdraw	Total	Total %	\$	%
ETH 100	980	30,110	29,222	59,332	18.51	6,526,668,183	76.05
ETH 10	989	45,005	43,854	88,859	27.72	1,019,418,269	11.88
ETH 1	989	51,583	48,874	100,457	31.34	115,189,485	1.34
ETH 0.1	989	25,869	22,043	47,912	14.95	4,485,031	0.05
DAI 100,000	516	3,345	3,125	6,470	2.02	334,500,000	3.90
DAI 10,000	516	2,935	2,785	5,720	1.78	29,350,000	0.34
DAI 1,000	980	1,078	952	2,030	0.63	1,078,000	0.01
DAI 100	989	232	182	414	0.13	23,200	< 0.01
cDAI 5,000,000	509	114	114	228	0.07	12,204,941	0.14
cDAI 500,000	507	87	85	172	0.05	930,423	0.01
cDAI 50,000	503	118	117	235	0.07	126,033	< 0.01
cDai 5,000	980	5	3	8	< 0.01	520	< 0.01
USDT 10,000	859	4	4	8	< 0.01	40,000	< 0.01
USDT 1,000	963	1,165	876	2,041	0.64	1,165,000	0.01
USDT 100	980	354	281	635	0.20	35,400	< 0.01
USDC 1,000	960	572	501	1,073	0.33	572,000	0.01
USDC 100	980	150	111	261	0.08	15,000	< 0.01
wBTC 10	510	1,202	1,190	2,392	0.75	495,206,202	5.77
wBTC 1	517	1,033	1,030	2,063	0.64	40,247,218	0.47
wBTC 0.1	503	142	136	278	0.09	589,046	0.01

NOTE: Deposit volume based on transactions, converted using daily ETH/USD and BTC/USD rates on Binance at time of deposit. Data extend up to Block 15,449,617, built on August 31, 2022, end of day UTC.

SOURCE: Ethereum blockchain / On-Chain Analysis.

August 2022 UTC (approximately three weeks after the OFAC sanction). Furthermore, for any deposit to a Tornado Cash pool we consider the depositor to be the account that initiated the transaction that led to the deposit. For example, if the deposit was made from a multi-sig wallet, the account that initiated the multi-sig transaction will be considered the depositor.

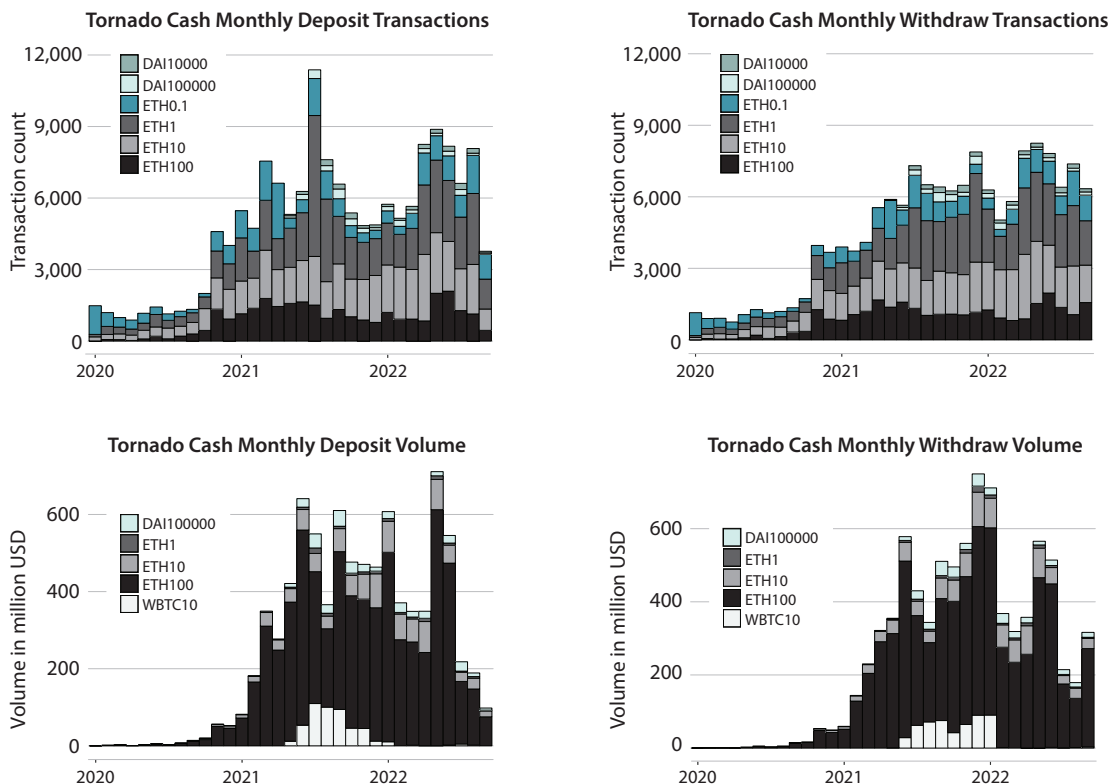
4.1 Usage

In total, assets equivalent to almost \$8.6 billion, valued at the time of deposit, have been deposited to the various Tornado Cash pools in 164,975 transactions. Table 1 shows how the usage is split across different pools.

The ETH pools are by far used the most, by transaction count as well as volume. The ETH 100 pool processed the most by volume, but the ETH 10 and ETH 1 pools are used more frequently. Stablecoins account for less than 5% of the total volume, as shown in Table 1.

Figure 2 shows the monthly deposit/withdrawal volumes and the monthly deposit/withdrawal transaction counts for all pools with more than 1% of the total value.

Figure 2
Transaction Count and Volume by Pool



NOTE: Deposits and withdrawals of the most popular Tornado Cash pools by transaction count and volume.
SOURCE: Ethereum blockchain / On-Chain Analysis.

4.2 Anonymity Set

Funds that go through a mixer are not necessarily untraceable. Users can make mistakes, and there are various ways in which the depositor and recipient addresses may become linked, if a user does not interact with the protocol as intended.

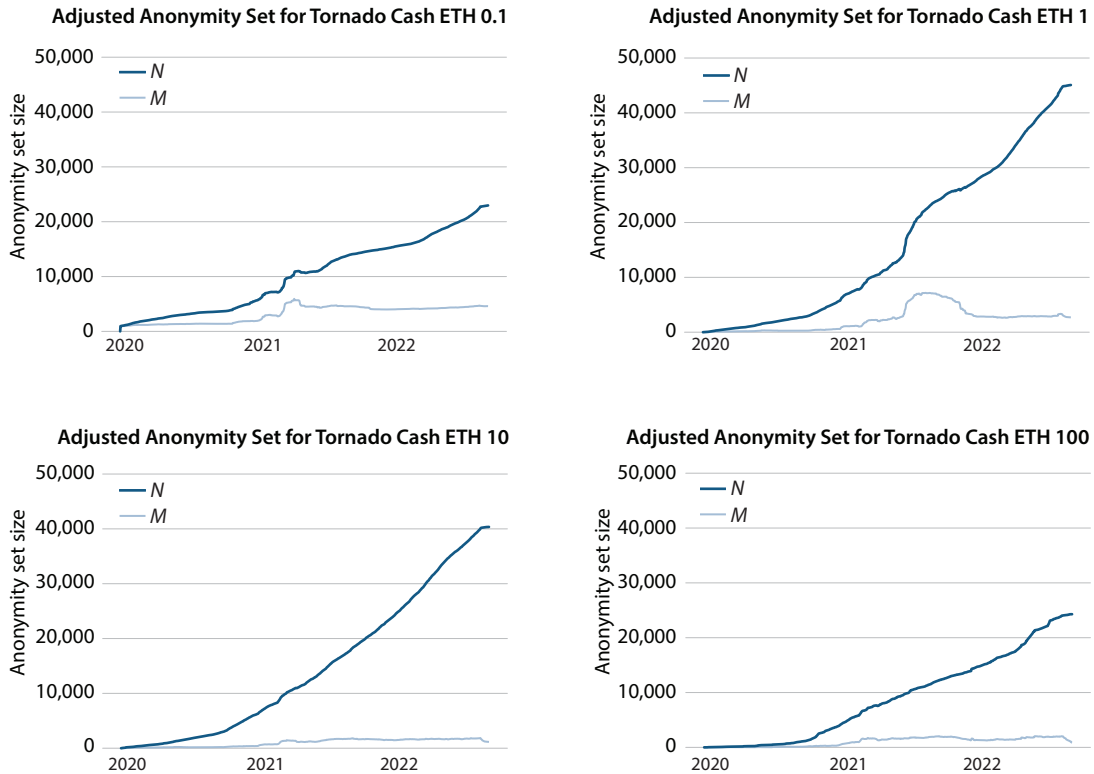
Béres et al. (2020) and Wu et al. (2022) have proposed various approaches to de-anonymize Tornado Cash transactions, making use of address re-use, transaction activity, transaction cost choice, or more complex transaction graph and network analyses. For a discussion on how to de-anonymize Tornado Cash transactions or an extended discussion on the anonymity set, refer to the above papers.

For our purposes here, we use a conservative approach and only link addresses, where the link can be established with certainty, i.e., cases where the same address is used for deposits and withdrawals. Similar to Wu et al. (2022), we find a significant number of actors that use the same address to deposit and withdraw their funds. While this seems surprising at first, there are various reasons why this may be the case, including but not limited to careless use of the protocol, testing transactions, or external incentive mechanisms.¹⁰

Figure 3 shows the adjusted anonymity set. At any point we know that there are M outstanding withdrawals that may belong to any one of N deposit addresses. If a person withdraws anonymously, this will lead to a decrease of M . N , on the other hand, is affected only if the link between deposit and

10. See <https://tornado-cash.medium.com/tornado-cash-governance-proposal-a55c5c7d0703>, especially the section “Anonymity Mining”

Figure 3
Deposit and Withdrawal—Adjusted Anonymity Set



NOTE: M is the number of outstanding withdrawals from the respective Tornado Cash ETH pool. N is the adjusted anonymity set: the number of deposit transactions that could be linked to a withdrawal transaction.

SOURCE: Ethereum blockchain / On-Chain Analysis.

withdrawal is publicly revealed, i.e., if the person does not preserve their anonymity. If M reaches 0 at any point, N will also be reset, as it becomes apparent that none of the previous deposits are still in the pool. At any point in time, M and N can be interpreted as follows: There are M outstanding deposits that belong to a subset of the anonymity set, which has N elements.

Additionally, Khovratovich and Vladimirov (2019) have pointed out that the reference to the Merkle roots may also have negative effects on the anonymity set. Suppose that there are currently 10 deposits and 5 withdrawals. Under normal circumstances, the 5 withdrawals could be from any depositor. However, if all withdrawals use a root value from a root state R_j , with $j \leq 5$, we know that all of the withdrawals link back to the initial 5 deposits.

5 DISCUSSION

In this section we discuss two important aspects of non-custodial crypto asset mixers. First, we analyze different types of privacy and suggest an approach how Tornado Cash might be usable in a regulated environment and allow honest users to benefit from partial privacy. Second, we discuss some regulatory challenges—namely, third-party tainting and redeployments.

5.1 Partial Privacy Proposal

The fundamental problem with any discussion around privacy is that there are good arguments for both sides. On the one hand, privacy-enhancing tools are being used by criminals and this is certainly an undesirable outcome. On the other hand, privacy may be desirable. For example, it may serve as an insurance against excessive centralization of power and contribute toward the resilience of a democratic system. An optimal solution will likely lie somewhere between perfect privacy and perfect observability. Ideally, the infrastructure would generate a separating equilibrium between honest and dishonest actors and allow the honest ones to remain partially private.

In the following section, we argue that Tornado-like privacy-enhancing tools might be able to generate such a separating equilibrium. We then introduce a conceptual framework to differentiate between various types of privacy and discuss potential outcomes of various policy responses.

Separating Equilibrium

Tornado Cash can break the observable link between a deposit and a withdrawal address, but it cannot hide the information that someone has received funds from a Tornado Cash pool. These data are clearly visible on-chain and can be collected and analyzed by anyone. Consequently, if Alice has received funds from a Tornado Cash address, any potential counterparty can see this information on the blockchain and decide if they want to interact with Alice.

Recall that there are two distinct reasons why Alice may have chosen to use Tornado Cash. In the first case, let's say Alice did indeed commit a crime and is using Tornado Cash to hide the fact that the funds originated from an illicit activity. In the second case, let's say the funds came from a legitimate source and Alice is using Tornado Cash to retain some privacy on the blockchain.

Regulation may want to differentiate between these two cases. We argue that there is a relatively straightforward way to generate a separating equilibrium. If Alice's funds come from a legitimate source, she can easily share a cryptographic proof that links her deposit to her withdrawal address.¹¹ She can choose with whom she would like this proof to be shared, allowing the counterparty to analyze the blockchain as if she had never used Tornado Cash. If for example, Alice wants to deposit funds with her bank, she could provide a cryptographic proof to the bank that allows them to analyze the transaction graph as if Alice had never used Tornado Cash. At the same time, Alice does not have to reveal her linked transaction history to the entire network.

In contrast, the bad-acting version of Alice—let's call her Malice—will not be able to provide this proof, as the disclosure of the link would reveal the illicit on-chain origin of Malice's funds to her counterparty.

Regulated financial intermediaries will only accept the funds if the customer is willing and able to provide proof of the funds' origins. Similarly, merchants who sell a good or service above a legal threshold value are legally obliged to file these transactions and have strong incentives to ask for a proof of origin. Otherwise, they might be in violation of the law and face challenges when trying to use the funds for which they cannot provide information about the origin.

This process creates a situation where honest actors can remain partially anonymous, while dishonest actors will face severe *search and matching* cost to find a counterparty that is willing to take the risk and accept the funds without the proof of origin. In fact, this is similar to how cash transactions are handled today. If someone wants to deposit cash with financial intermediaries or use large amounts of cash to pay for goods or services, they have to provide a proof of origin for the funds. Blockchain-based non-custodial crypto asset mixers allow for an easier and more reliable proof than cash-based transactions.

11. The standard frontend for Tornado Cash has provided a compliance tool, allowing the user to generate a report, including the cryptographic proof.

Table 2
Privacy Assessment by Regulatory Scheme

	Public chain privacy	Counterparty privacy	
		Backward-looking	Forward-looking
No mixing protocols	—	—	—
Mixing with partial disclosure	✓	—	✓*
Mixing with no disclosure	✓	✓	✓

NOTE: A comparison of privacy properties under various policy responses to non-custodial crypto asset mixers.

*Conditional on another ex-post privacy-enhancing event.

Note, that the use of a non-custodial crypto asset mixer is not free. Any smart contract interaction is subject to transaction fees. Moreover, the switch to a new address may require new token approvals (see ERC-20 token standard¹²), which are also subject to a transaction fee. While it is important to be aware of the existence of these costs, they can be mitigated, depending on the scalability properties of the blockchain or a switch to a layer 2, i.e., a scalability solution built on top of the blockchain network.

Forward- vs. Backward-Looking Privacy

A regulatory regime built around voluntary disclosure would allow Alice to use privacy-enhancing protocols by sharing some information with her specific counterparty. For obvious reasons, this voluntary disclosure scheme is not a perfect privacy solution. However, it allows honest actors to retain partial privacy and to choose with whom they want to share (parts of) their transaction graph.

To understand the exact implications of this approach, it might be useful to differentiate between *forward-looking privacy* and *backward-looking privacy*. We define the terms as follows: A privacy-enhancing event satisfies forward-looking privacy if it does not allow the observer to link a known transaction that occurred before the privacy-enhancing event to future transactions that happen after the privacy-enhancing event. Similarly, a privacy-enhancing event satisfies backward-looking privacy if it does not allow the observer to link a known transaction that occurred after the privacy-enhancing event to past transactions that happened before the privacy-enhancing event.

The voluntary disclosure scheme is very limited with respect to backward-looking privacy. If Alice is asked to share proof that allows the counterparty to link her current address to the pre-mixing address, that counterparty would be able to look back and scrutinize Alice's transaction history. For forward-looking privacy, however, Alice can simply run her funds through a new privacy-enhancing event. If her interactions with the counterparty are concluded, there is no reason to disclose the new proof to that specific counterparty. Thus, forward-looking privacy can be established.

Table 2 shows the privacy implications of various policy decisions. In a world without any privacy-enhancing protocols, the entire transaction history would be visible on the blockchain. Anyone could observe every single transaction. Privacy would be nonexistent.

In a world with no restrictions on the use of privacy-enhancing protocols, it would be possible to achieve public chain privacy and both forms of counterparty privacy, i.e., forward- and backward-looking. However, it would not be possible for a counterparty to observe if they are accepting funds that have previously been used in illicit activities.

A scheme that is based on privacy-enhancing protocols and voluntary disclosure would allow public chain privacy and forward-looking privacy, with respect to the specific counterparty.

12. A standard interface for fungible tokens on Ethereum, see <https://github.com/ethereum/EIPs/blob/master/EIPS/eip-20.md>

Practical Examples

Example 1: Let us assume that Bob has withdrawn crypto assets from custody with a regulated financial intermediary and stores these assets on his non-custodial wallet. He decides to subsequently use a non-custodial crypto asset mixer to break the publicly observable link between the custodian and his current address. Neither the custodian nor anyone else will be able to link the Tornado Cash deposit to the Tornado Cash withdrawal. He then uses his new address to buy something from merchant Alice. Alice observes the blockchain and can easily see that the funds originate from a Tornado Cash pool. She will ask for a cryptographic proof that allows her to link the Tornado Cash withdrawal to a deposit and observes that the funds originate from a legitimate source. Alice stores this proof.

To ensure that Bob cannot observe her future transactions, Alice decides to use Tornado Cash herself, thereby establishing forward-looking privacy against Bob. When she later wants to use the funds, her counterparty will ask for the proof of her Tornado Cash interaction, as well as the proof of the previous Tornado Cash interaction, allowing the counterparty to trace the payment back to the point when it was last held by a centralized entity.

Example 2: Let us assume that Alice uses 10 distinct non-custodial addresses for various on-chain activities. She wants to consolidate these addresses and deposit the funds with a custodian. In the absence of a crypto asset mixer, anyone could easily see that the funds from these 10 accounts are sent to the same address. Anyone, particularly those who have interacted with one of Alice's addresses, could easily come to the conclusion that the other 9 addresses must also belong to Alice and analyze every single one of her past transactions across multiple accounts. A non-custodial crypto asset mixer would allow Alice to break the link between these accounts and share the information only with the party who needs to know about the funds' origin, i.e., the custodian.

5.2 Regulatory Challenges

Third-Party Tainting

Funds deposited in a non-custodial crypto asset mixer can be withdrawn to any address and, critically, there is no way to reject or block such a transaction if the recipient does not wish to receive mixed funds. Receiving funds from a sanctioned entity is a criminal offense. A malicious actor could therefore send their funds to a sanctioned, non-custodial crypto asset mixer and withdraw them to addresses that are publicly associated with another entity. For an observer, there is no way to determine whether the receiving party interacted with the mixer or not; and the receiving party will not be able to prove they were not involved. Recall that, while it is possible to demonstrate you interacted with the mixer via the cryptographic proof, it is impossible to show that you are not in possession of such a proof. The burden is placed on the receiving party who must act and try to resolve the situation. One potential way of doing so is to provably dispose of the tainted assets in a way that is publicly observable. In a blockchain context, this means to send an amount equal to the received funds to a known and accepted "burn address"—an address where no one controls the private key. The measure is not perfect, as it would still place a burden in the form of a mandatory action and transaction fees on the receiving party, but at least it would not allow a third party to freeze someone else's address or generate legal trouble. The OFAC has acknowledged this form of attack and addressed it on November 8, 2022, in an addendum to the Tornado Cash sanctions, stating that they will not prioritize enforcement regarding these "dusting" transactions.¹³

Further questions arise in any smart contract protocol that acts as an open marketplace with peer-to-peer sales or auctions. The problem here is that the seller has no control over the origin of the assets they receive and no information about the identity of the buyer. To mitigate this, the marketplace would have to restrict the participants and only allow users with a confirmed identity.

13. See <https://home.treasury.gov/policy-issues/financial-sanctions/faqs/1078>

Redeployment

One of the goals of sanctions is to elicit a change of behavior from the sanctioned entity. Smart contract-based protocols without privileged access are immutable and therefore not capable of changing their behavior by design. Sanctions in this context are more akin to a ban of the protocol.

Smart contracts are deployed and stored in the form of code on the blockchain. The code for each smart contract is public and can be read directly from the blockchain. This makes it trivial for anyone to copy and redeploy a new instance of any protocol at a different address. As a result, regulatory actions against a specific smart contract address are at best a temporary solution. Redeployments with identical code will force frequent updates of a sanctions list and lead to a game of “whack-a-mole.”

Slight variations in the code can make the situation even more challenging, as it may be unclear if something is a functional copy of a sanctioned protocol or a new implementation that must be treated and analyzed separately.

In contrast, regulating on- and off-ramps would have the advantage that it places the burden of proof on the individual who wants to transfer the funds to the financial intermediary.

6 CONCLUSION

Privacy-enhancing protocols are a very interesting innovation, with pros and cons. On the one hand, privacy may be desirable and is not necessarily associated with illicit activity. On the other hand, there is strong evidence that privacy-enhancing protocols such as Tornado Cash are also used by malicious actors and may potentially allow them to cover their tracks.

The policy action set is bounded by the two extreme choices: (i) not allowing any interactions with privacy-enhancing protocols and (ii) accepting all funds from privacy-enhancing protocols, with no questions asked. We argue that neither of these extreme responses constitutes a good strategy. There are various reasons why someone chooses to interact with a privacy-enhancing protocol. Any extreme choice ignores the existence of these different use cases and creates an inefficient outcome. An optimal solution will likely lie somewhere between perfect privacy and perfect observability.

Consequently, we suggest an approach that could potentially create a separating equilibrium that allows honest participants to achieve partial privacy. Moreover, we propose a distinction between different types of privacy, namely, public chain privacy as well as forward-looking and backward-looking counterparty privacy.

It is important to highlight the fact that a user of privacy-enhancing protocols can voluntarily share information with any third party. This information can contain a cryptographic proof that reveals how their withdrawal transaction is linked to a prior deposit. The entity that receives this information can verify the proof mathematically and analyze the user’s transaction graph as if they had never used the privacy-enhancing protocol. Yet, the user does not have to share this information publicly, allowing them to preserve public chain privacy.

Financial intermediaries (or merchants in case of a large sale) may ask for this proof. The approach essentially treats the privacy-enhancing protocol as an independent protocol and regulates the on- and off-ramps. This is similar to how cash transactions are regulated, with the big difference that cash does not involve an immutable transaction history. As such, a blockchain proof is much more reliable than any proof that involves cash.

We conclude that non-custodial crypto asset mixers are an interesting innovation and demonstrate the power of zero knowledge proofs. They provide honest users with the option not to share their transaction history publicly and use public blockchains similarly to other electronic payment systems.

Yet, the risks are real and should also not be underestimated. Some level of regulation is necessary and perfect privacy will not be possible in a regulated environment. It is crucial to regulate on- and off-ramps (including centralized on-chain protocols) and enforce AML (anti-money laundering) and CFT (combating the financing of terrorism) regulations through these intermediaries. If this is done properly, crypto asset mixers such as Tornado Cash may become an integral part of public blockchain infrastructure.

REFERENCES

- Berentsen, Aleksander and Schär, Fabian. "A Short Introduction to the World of Cryptocurrencies." Federal Reserve Bank of St. Louis *Review*, First Quarter 2018, pp. 1-16; <https://doi.org/10.20955/r.2018.1-16>.
- Berentsen, Aleksander et al. "A Walk-through of a Simple Zk-STARK Proof." 2022; <http://dx.doi.org/10.2139/ssrn.4308637>.
- Béres, Ferenc et al. "Blockchain Is Watching You: Profiling and De-anonymizing Ethereum Users." 2020; <https://arxiv.org/abs/2005.14051>.
- Buterin, Vitalik. "Ethereum: A Next-Generation Smart Contract and Decentralized Application Platform." 2014; https://ethereum.org/669c9e2e2027310b6b3cdce6e1c52962/Ethereum_Whitepaper_-_Buterin_2014.pdf.
- Khovratovich, Dmitry and Vladimirov, Mikhail. "Tornado Privacy Solution Cryptographic Review Version 1.1." 2019; retrieved August 15, 2022, before being taken offline; https://web.archive.org/web/20220808144457/https://tornado.cash/audits/TornadoCash_cryptographic_review_ABDK.pdf.
- Petkus, Maksym. "Why and How zk-SNARK Works: Definitive Explanation." 2019; <https://arxiv.org/abs/1906.07221>.
- Schär, Fabian. "Decentralized Finance: On Blockchain- and Smart Contract-Based Financial Markets." Federal Reserve Bank of St. Louis *Review*, Second Quarter 2021, pp. 153-74; <https://doi.org/10.20955/r.103.153-74>.
- Thaler, Justin. "Proofs, Arguments, and Zero Knowledge." 2022; <https://people.cs.georgetown.edu/jthaler/ProofsArgsAndZK.pdf>.
- Szabo, Nick. "Smart Contracts." 1994; <http://www.fon.hum.uva.nl/rob/Courses/InformationInSpeech/CDROM/Literature/LOTwinterschool2006/szabo.best.vwh.net/smart.contracts.html>.
- Szabo, Nick. "The Idea of Smart Contracts." 1997; <https://nakamotoinstitute.org/the-idea-of-smart-contracts/>.
- Wood, Gavin. "Ethereum: A Secure Decentralised Generalised Transaction Ledger." 2015; <https://ethereum.github.io/yellowpaper/paper.pdf>.
- Wu, Mike et al. "Tutela: An Open-Source Tool for Assessing User-Privacy on Ethereum and Tornado Cash." 2022; <https://arxiv.org/abs/2201.06811>.