Fraud Across Borders*

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April 5, 2022

Abstract

We build a theoretical framework for cross-border fraud in which international fraud complaints follow a gravity model. Using several large databases of consumer complaints, we find that complaints exhibit gravity; compared to trade volumes, cultural distance is more important for complaints and physical distance less important. We then use the gravity model estimates to estimate country-level fraud rates and identify clusters of countries with high fraud rates. Finally, in line with our model predictions, high fraud rates are negatively correlated with per-capita GDP and measures of strong regulatory institutions.

Keywords: gravity, fraud, complaints, international trade

*The views expressed in this article are those of the authors. They do not necessarily represent those of the Federal Trade Commission or any of its Commissioners. We thank Doug McKenney, Hui Ling Goh, Paul Witt, and the Australian Competition and Consumer Commission for helping to provide data for this project. We also thank Jasmina Chauvin, Marguerite DeLiema, Keith Head, Fariha Kamal, Ferdinando Monte, Ezra Oberfield, Dave Schmidt, Yaying Zhou, and participants at the Southern Economic Association and Society of Government Economists conferences for their comments.

> *Attention My Dear,*
>
> *You have been a lucky winner of $3.2 MILLION from western union west Africa continent as value customer who use western union to transfer money from one country to another. ... To Enable him send your First Payment of $5000 today.*[1]

The above email excerpt is one example of the famous "Nigerian Prince" scam. The victim just needs to wire an initial payment to Nigeria in return for a large cash payout. Of course, the promised millions never arrive.

Globalization, together with the rise of the Internet, has made such cross border fraud increasingly common. Exposés have shown how international crime rings target consumers in rich Western countries for fraud (Shadel and Wertheimer, 2021; Mclean, 2020). To give a sense of the scale of the problem, in recent years the Federal Trade Commission (FTC) obtained over $700 million in settlements against Western Union and MoneyGram, alleging that these companies should have done more to prevent international fraud-related money transfers (Federal Trade Commission, 2017, 2018).[2]

Despite its prevalence, however, we still know little about cross-border fraud. What countries disproportionately contribute to such fraud? What are its underlying determinants? The FTC has invested millions of dollars in building consumer complaint databases, including a worldwide colloborative effort specific to international fraud, to help answer these questions and allow enforcers to better target their efforts to crack down on fraud.

In this paper, we use databases of consumer complaints to identify country-level fraud rates. Our approach is based on an economic model of cross-border fraud in which consumer complaints display gravity. We test the model's predictions of the underlying determinants of cross-border fraud using the estimated country-level fraud index.

[1] See `https://historycollection.com/the-nigerian-prince-scam-is-actually-hundreds-of-years-old-but-continues-to-scam-people-today/11/`.

[2] The FTC's complaint against Western Union, for example, specifically pointed to hundred of millions of dollars in fraud-related transfers paid out to agents in many countries, including Mexico, Nigeria, the United Kingdom, Jamaica, Peru, Ghana, and Spain. Similarly, the FTC complaint against MoneyGram documented tens of millions of dollars lost to cross-border fraud during the time period under investigation.

We first develop a version of an Armington model of trade that allows for fraud. In the model, firms choose how much to defraud consumers. The country-level fraud rate has a simple, closed form solution, with higher fraud rates in countries with worse fraud enforcement or with firms that are more "productive" at fraud. Some defrauded consumers complain; in the model these complaints, like trade flows, exhibit gravity.

To measure fraud, we exploit the Consumer Sentinel Network, a unique, massive database of consumer complaints developed for law enforcement purposes. This database compiles complaints from dozens of contributors, including government agencies such as the FTC, NGOs such as the Better Business Bureaus (BBB), private companies like MoneyGram and Western Union, and `econsumer.gov`, a collaborative effort of enforcers across the globe. Because each complaint includes the address of the complaining consumer and the business that they complain about, we can construct country-country pairs to estimate a gravity model. This database has more than 14 million complaints from 2014 to 2021, including almost a million cross-border complaints.

We supplement the Consumer Sentinel dataset with two additional datasets of complaints. First, we obtain the worldwide database of complaints for a decade for a large money transfer network, including information on the sending and receiving agent location for every money transfer with a complaint. Unlike Consumer Sentinel, this dataset does not rely on consumers accurately reporting the address of the company that defrauded them. Second, we also analyze three and a half years of complaints filed with the Australian Competition and Consumer Commission (ACCC). The ACCC mostly receives complaints from Australian consumers rather than American consumers like Consumer Sentinel.

We then estimate a gravity model for complaint data using a pseudo likelihood Poisson model (Silva and Tenreyro, 2006). Gravity holds for complaints, just as it does for trade volume. However, cultural distance matters more, and physical distance less, for complaints. In our baseline specification, complaints decline by 4.3% with a 10% increase in physical distance, compared to 7.5% for trade volumes over the same time period. Unlike trade flows, complaints are not more common across contiguous country boundaries. Complaints exhibit cultural gravity, increasing by 85% with common language, compared to only 27% for trade volumes.

In our model, the difference in the origin country fixed effect in gravity equations of complaint and trade volumes identifies the country level fraud rate. We thus develop a country-level fraud index based upon our gravity estimates. Jamaica, Benin, and Gambia have the highest fraud rates, with the Caribbean and West Africa as hotspots for fraud. In contrast, South America, the Middle East, and Europe have lower fraud rates than the world average.

We then test the model's predictions on the determinants of fraud across countries. We use World Bank measures of the quality of governance across countries as proxies for the level of enforcement, and per capita GDP as a proxy for the relative cost of fraud. Consistent with the model, our estimated fraud rates are negatively correlated with per-capita GDP and measures of the quality of governance. However, after controlling for both variables, only per capita GDP has a statistically significant correlation with the fraud index.

Our paper contributes to an emerging body of work on how criminal activity affects domestic and international trade. Economists have examined the effects of counterfeiting both theoretically (Grossman and Shapiro, 1988), as well as empirically using data from the Chinese dairy industry (Qian, 2008) and trademark regulation affecting foreign firms active in pre-war Shanghai (Alfaro et al., 2022). Others have examined how adulteration and contamination of products affects sales of milk in China (Bai, Gazze and Wang, 2021) and the global pharmaceutical trade (Feng, 2020). Rising online sales may exacerbate these issues if consumers are unable to distinguish between high quality and low quality sellers on online platforms (Bai et al., 2020). Criminals also launder their ill-gotten gains internationally; Ferwerda et al. (2013) and Ferwerda et al. (2020) predict illicit financial flows by estimating a gravity model based upon suspicious US trade flows and transactions to and from the Netherlands, respectively.

We also add to a small but growing literature on fraud victimization and consumer complaints as a measure of such victimization. Anderson (2017) reports that 16% of Americans fall victim to fraud each year, with losses in the billions of dollars; Dijk, Kesteren and Smit (2007) find similar rates of fraud internationally. One strand of the literature has focused on the demographics of victims, and how complaining varies with demographics (Raval, 2020*b*,*a*, 2021).[3] Another strand has looked at the role of market structure following Hirschman (1970), and found more complaining in more concentrated markets (Beard, Macher and Mayo, 2015; Gans, Goldfarb and Lederman, 2021).

Finally, our paper adds a new example of gravity in spatial markets. The gravity equation in trade arises naturally out of several economic models (Bergstrand, 1985; Head and Mayer, 2013; Arkolakis, Costinot and Rodríguez-Clare, 2012), with gravity perhaps one of the most studied findings in empirical economics (Anderson and Van Wincoop, 2004; Anderson, 2011). In addition, a gravity equation has been documented by Hortaçsu, Martínez-Jerez and Douglas (2009) for online commerce, Grogger and Hanson (2011) for migration, Helpman, Melitz and Yeaple (2004) for foreign direct investment, and Wolf (2000) for domestic trade.

The paper proceeds as follows. Section 1 details our data on complaints, Section 2 builds a theoretical model that derives a gravity equation for complaints, and Section 3 estimates the gravity model. Section 4 builds a country specific fraud index based on the complaints, and Section 5 concludes.

1 Complaints Data

1.1 Consumer Sentinel

Our primary source of data is the Consumer Sentinel Network, which collects information on consumer complaints. These complaints come from federal government agencies such as the Federal Trade Commission and Consumer Financial Protection Bureau; private sector

[3] Sweeting et al. (2020) summarizes this work.

organizations such as the Better Business Bureaus (BBBs); state and local government agencies such as state attorneys general and police departments; and private companies such as Western Union and MoneyGram.[4] We use data from 2014 to 2021.

Each complaint in the Consumer Sentinel data has information on the consumer as well as the company. Importantly for our purposes, the country names of the consumer and the company are listed in the data. We exclude complaints that are missing either of these country names.[5]

Table 1 shows the distribution of complaints across the primary data sources of international complaints.[6] The first column details all complaints and the second column complaints with a US consumer or company. The third column details "cross-border" complaints; that is, complaints where the consumer lived in a different country than the company. Over the time period we study there are over 14 million complaints across all sources. As shown in the second column, the vast majority—98 percent—listed a consumer or a company in the United States. Still, given the sheer number of complaints, over 350,000 complaints did not involve the United States at all, and almost a million involved two different countries.

The remaining rows show how these complaints were distributed across the primary data sources. The FTC is the largest individual contributor to Consumer Sentinel, with about one third of all complaints and a similar share of both US based and cross-border complaints. Consumers can complain about fraud and other issues online at `reportfraud.ftc.gov` or via a toll free number; consumers from any country are allowed to complain. In addition, consumers can complain specifically about international scams on `econsumer.gov`, an initiative of the International Consumer Protection and Enforcement Network (ICPEN),

[4]See https://www.ftc.gov/enforcement/consumer-sentinel-network/reports for the Consumer Sentinel Data Book, which contains further detail on the Consumer Sentinel and statistics on the complaints included in it.

[5]We omitted data from one source, Privacy Star, because it does not consistently provide geographic information. There may be multiple observations per complaint because several individuals were harmed by the same instance of a company's behavior. To account for these potential duplicates, we keep each unique combination of consumer country and company country within complaint. Our results are robust to alternative approaches. Overall, 11.8 percent of records in Consumer Sentinel were missing a company or consumer country record, the vast majority of these (97 percent) due to a lack of a company country record.

[6]Over 270 other individual data sources have been aggregated into the "Other" category.

to gather and share consumer complaints about international scams. The econsumer.gov website is available in several languages and allows law enforcement around the world to share and access consumer complaint data and other investigative information.

The BBB and the CFPB are the second and third largest sources of complaints; together with the FTC, they account for three quarters of all complaints in the data. However, the BBB and CFPB have a much smaller share of their complaints across borders; only 9% of cross-border complaints are from the BBB, and 1% from the CFPB, compared to 27% and 17% for US based complaints.

The remaining cross-border complaints come from three broad groups of sources. The first group focuses on internet-related fraud and other crime. The Internet Crime Complaint Center (IC3), run by the FBI, gathers complaints about internet-related criminal activity, including fraud, hacking, money laundering, etc. The Microsoft Cyber Crime Center, now known as the Digital Crimes Unit (DCU), is a similar effort as the IC3. The DCU focuses on activity related to child trafficking, as well as activity related to ransomware, malware, tech support frauds, and email fraud. Together, these two sources account for just seven percent of all complaints, but 22 percent of all cross-border complaints.

The second group of sources includes the money transfer companies Western Union and MoneyGram. Athough these companies are US-based, they operate globally, and so have a larger proportion of their complaints filed without a US-based consumer or about a US-based company. In addition, these companies will have information on the sending location and receiving location for all money transfers with complaints, so we do not have to worry about missing company locations. These two sources represent another 22 percent of all cross-border complaints.

Finally, the US Postal Inspection Service is the law enforcement arm of the US Postal Service, and records activity related to mail fraud. Almost all of the complaints are US-based, but a large proportion have an international component as well.

Together, the data in the Consumer Sentinel includes a large number of international complaints. Moreover, because the sources of the data vary from cybercrime to wire fraud, they give us a rich understanding of the extent of international fraud throughout the time period we study.

Table 1: Distribution of Complaints Across Sources

	(1) Total	(2) US-Based	(3) Cross-Border
Total Complaints (N)	14679775	14319950	925449
US FTC	0.33	0.34	0.35
BBB	0.27	0.27	0.09
US CFPB	0.16	0.17	0.01
Internet Crime Complaint Center	0.04	0.04	0.10
Microsoft Cyber Crime Center	0.03	0.02	0.12
MoneyGram	0.02	0.02	0.15
Western Union	0.01	0.01	0.07
US Postal Inspection Service	0.01	0.01	0.04
Other	0.12	0.13	0.07

Notes. The table shows the total number of complaints and the share of complaints at each data source. The US-based column shows the number of complaints that include the US as either a consumer or company. The cross-border column is the number of complaints that include different consumer and company countries.

1.2 A Large Money Transfer Company

In addition to the Consumer Sentinel data, we also use a complementary data source in the internal complaint database from a large money transfer company, which we term "MT" for simplicity. A potential weakness of the Consumer Sentinel data is that consumers may not always know who defrauded them, and so cannot put down the country that the company was located in, or may identify this country with error. For example, the victim of a tech support scam might report that the scammers had foreign accents, but not know their exact country.

With the MT data, we have the location for almost all money transfers of the sending country agent and receiving country agent, which reduces the problem of missing company location.[7] In addition, we can examine both the number of complaints and the dollar value of financial flows from complaints. The complaints in the MT dataset are from 2004 to 2014.

[7] Overall, just 5.9 percent of complaints were missing a company or consumer location.

One potential caveat of this data, however, is we may only observe the initial leg of the supply chain of fraud. For example, a scammer might receive a wire transfer related to fraud and then immediately transfer that money to another location; we would only observe the location of the receiving agent for the first transfer.

1.3 Australian Competition and Consumer Commission

Another potential weakness of the Consumer Sentinel database is its US focus; the largest contributors are US government agencies and nonprofits such as the BBB based in the US. Even the money transfer agencies such as Western Union and MoneyGram are headquartered in the US, even if their business is global.

We thus also add information from all fraud related complaints from the Australian Competition and Consumer Commission (ACCC) from 2018 through the first half of 2021.[8] These data include complaints from Australian consumers or about entities claiming to be Australian. Thus, the ACCC data allow us to examine whether American consumers have different patterns of cross-border fraud than consumers in other countries.

1.4 Data Coverage

Overall, the sample consisted of almost 15 million complaints filed with Consumer Sentinel, almost 400,000 filed with MT, and approximately 460,000 filed with the ACCC. Across the three datasets and all sources within Consumer Sentinel, the complaints encompassed a wide array of types of fraud and other schemes. Table 2 shows the share of cross-border complaints in the most common complaint categories within the Consumer Sentinel and MT data.[9] The second column of the table shows the share of US domestic complaints—that is,

[8] See `https://www.scamwatch.gov.au/scam-statistics` for statistics on these complaints. The ACCC has recently become a contributor to Consumer Sentinel, although its complaints in the Sentinel database were added very recently and so are not included in the Consumer Sentinel data we analyze in this paper.

[9] The ACCC data we were provided does not include complaint category. The Consumer Sentinel and MT data have different complaint category definitions and so are not directly comparable. Table A1 and Table A2 show a longer list of complaint categories for both data sources.

with a US-based consumer and company—within the category for comparison.

Panel A of Table 2 shows that imposter scams, such as the Nigerian Prince scam, comprise more than one quarter of all cross-border complaints in the data. The second largest group of scams concerned online shopping, such as consumers not receiving products or receiving broken or incorrect products. The remaining categories have much smaller shares, with prizes and sweepstakes, internet services, and counterfeit check scams as the next three largest scams with four to six percent of cross-border complaints each. On the other hand, less than one percent of cross-border complaints concerned banks, debt collection, and credit ratings, which are a much larger share of US based complaints.

The second panel of the table shows the largest categories for the MT data. Online purchases were the largest type of cross-border complaint, comprising about 25 percent of all cross-border complaints. Prizes, advanced fee scams, romance scams, and fraud related to emergencies and natural disasters round out the next four categories.

Table 2: Most Common Complaint Categories

	(1) Cross-Border	(2) US Domestic
A. Consumer Sentinel		
Imposter Scams	0.255	0.171
Online Shopping, Catalog Sales, and Negative Reviews	0.208	0.069
Prizes, Sweepstakes and Lotteries	0.060	0.058
Internet Services	0.040	0.032
Fake/Counterfeit Check Scams	0.039	0.012
B. MT Data		
On-Line Purchases	0.257	0.361
Lottery/Prize	0.147	0.093
Advance Fee/Prepayment	0.116	0.071
On-Line Relationship	0.097	0.028
Emergency Funds	0.090	0.042

Notes. The table shows the share of complaints by category. The US-based column shows the number of complaints that include the US as consumer and company. The cross-border column is the number of complaints that include different consumer and company countries. "Online Shopping, Catalog Sales, and Negative Reviews" and "Shop-at-home and Catalog Sales" were combined into one category because of a renaming in the data. "Fake Check Scams" and "Counterfeit Check Scams" have also been combined into one category.

We collapse the Consumer Sentinel, MT, and ACCC complaints data to a dataset with each possible country-country pair, including same-country pairs. Each country in the pair is represented twice, once as the consumer country and once as the company country. For example, complaints about US companies from German consumers would be a different pair than complaints about German companies from US consumers. Table 3 shows basic summary statistics about the resulting dataset.

In Consumer Sentinel, about 15% or 10,000 of these pairs had a non zero number of complaints.[10] Almost all pairs with a US consumer or country had non-zero complaints; the vast majority of complaints involved a US consumer or company.[11] In addition, three quarters of countries had at least one complaint from a consumer to a company based in the same country (e.g. a German consumer and a German company).

The MT data is more limited in scope than the Consumer Sentinel data, accounting for only three percent of all possible country-country pairs. This likely reflects, in part, the flow of money transfers across borders. Still, this data source contained information on most flows between US consumers and other countries.

The ACCC data only includes country pairs where either the consumer's country or the company's country is Australia. This data thus cover very few of all the possible pairs. Nevertheless, the data do include complaints from 128 countries about Australian companies, and complaints from Australian consumers about companies in 223 countries, which are comparable to the Consumer Sentinel coverage of complaints from US consumers about non-US companies.

Finally, as a point of comparison, Table 3 shows the coverage of the ITC trade data that we use for the gravity analysis. This database has detailed information on sector-level trade flows between all countries. Over half of the possible pairs are populated, as well as over half of the cross-border pairs. Interestingly, the ITC data has slightly worse coverage than

[10] With 252 countries, there were 63,504 possible country-country pairs.

[11] The single US-US pair comprised 92% of all complaints, and pairs where either the consumer or the company was in the United States were another 5% of all complaints,

the Consumer Sentinel data for US-based pairs.

Table 3: Pairs and Total Complaints, by Consumer and Company Country

	(1) Possible Pairs	(2) CS	(3) MT	(4) ACCC	(5) ITC Trade
Total	63504	0.151	0.033	0.006	0.524
US Company, non-US Consumer	251	0.936	0.434	0.004	0.892
Non-US Company, US Consumer	251	0.944	0.801	0.004	0.880
Cross-Border Pair	63252	0.148	0.032	0.006	0.524
Same-Country Pair	252	0.754	0.333	0.004	0.635

Notes. Column 1 shows the total number of pairs of countries in a datset with 252 countries, including same-country pairs. Columns 2-5 show the percentage of possible pairs with non-zero numbers of complaints (in columns 2 and 3) and trade volume (in column 4). Column 2 shows data from Consumer Sentinel from 2014-2021, column 3 shows data from MT data only, from 2004-2014, column 4 shows data from the ACCC, and column 5 shows trade volume data from the International Trade Commission trade data since 2014.

In order to understand how fraud rates vary across complaints, we need to interpret this data on complaints through the lens of an economic model; simply creating a list of the countries that receive the most complaints is not sufficient. To illustrate this point, Table 4 shows a ranked list of the 25 countries that received the most complaints throughout the entire time period, 2014-2021, across all sources in the Consumer Sentinel data. The United States dwarfs all other countries, in large part because many of the data sources at our disposal focus on domestic American complaints, but also because the United States is the world's largest economy. Similarly, other large economies, such as China, the United Kingdom, Germany, and France also make the list. On the other hand, some countries stand out. Nigeria, Jamaica, the Philippines, and Ghana are all countries that have previously been tied to a proliferation of fraud schemes. In order to do so, we develop an economic model in the next section that allows us to identify fraud rates from the complaint data.

2 Model

We begin by developing a model of cross-border fraud. As Table 2 shows, cross-border fraud includes many different types of activities. For simplicity, we focus on the potentially

Table 4: Countries with Most Complaints, Consumer Sentinel

Country	Complaints
UNITED STATES	13912818
CANADA	171489
CHINA	78736
UNITED KINGDOM	61937
INDIA	51195
NIGERIA	48639
JAMAICA	30880
MEXICO	25267
GERMANY	17097
FRANCE	16559
PHILIPPINES	15490
GHANA	13676
SPAIN	13525
AUSTRALIA	11582
HONG KONG	9739
SOUTH AFRICA	8618
DOMINICAN REPUBLIC	7888
TURKEY	7705
BENIN	7677
CAMEROON	7609
NETHERLANDS	7459
UKRAINE	6182
MALAYSIA	5670
COTE D'IVOIRE	5289
RUSSIAN FEDERATION	5285

Notes. The table shows the 25 countries with the most complaints filed in Consumer Sentinel, 2014-2021, across all sources, about a company based in that country.

fraudulent sale of a product across borders; online shopping is one of the top categories for complaints in both the Consumer Sentinel and MT data.

Our theoretical framework is based upon the Armington trade model. We show that fraud complaints obey a gravity equation, and the fixed effects from the gravity equation can be used to identify the level of fraud from a country. The model has a simple, intuitive closed form for the degree of fraud in each country.

There are S countries, where origin countries are indexed by i and destination countries by j. Each country produces its own variety of a good. Thus, a consumer complaint on fraud would involve a consumer in country j complaining about the variety from country i.

Producers in each country play a mixed strategy over providing a high quality good h and committing fraud by providing low quality good l. Producers in country i play l with probability f_{ij}. Consumers receive no value from the low quality good l, so consumers in i buying q_{ij} receive $(1-f_{ij})q_{ij} = q^*_{ij}$.

2.1 Demand

Consumers have Dixit-Stiglitz preferences over goods:

$$
\begin{aligned}
U_j &= (\sum_{i\in S} a_{ij}^{1/\sigma}(q^*_{ij})^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} && (1)\\
&= (\sum_{i\in S} a_{ij}^{1/\sigma}(1-f_{ij})^{\frac{\sigma-1}{\sigma}} q_{ij}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}, && (2)
\end{aligned}
$$

where σ is the elasticity of substitution between varieties and a_{ij} is a preference parameter for how much consumers in country j like products in country i.

Consumers maximize utility subject to their budget constraint. Demand is thus:

$$q_{ij} = a_{ij}(\frac{p_{ij}}{1-f_{ij}})^{-\sigma}(1-f_{ij})^{-1}P_j^{\sigma-1}E_j \tag{3}$$

where E_j is the expenditure of country j and P_j is the Dixit-Stiglitz price index:

$$P_j = (\sum_k a_{kj}(\frac{p_{kj}}{1-f_{kj}})^{1-\sigma})^{\frac{1}{1-\sigma}} \tag{4}$$

If we consider the fraud-adjusted price $p^*_{ij} = \frac{p_{ij}}{1-f_{ij}}$ and fraud-adjusted quantity $q^*_{ij} = (1-f_{ij})q_{ij}$, demand has the standard Dixit-Stiglitz form in p^*_{ij} and q^*_{ij}.

2.2 Supply With Fraud

The firm can produce the high quality good at cost c^h and the low quality good at cost c^l. We assume that $c^h > c^l$, so it is cheaper for the company to produce the fraudulent good. Shipping the good abroad entails iceberg trade cost τ_{ij}.

A regulator detects fraud and fines a company with probability $d(f) = df$ where $d \in (0, 1)$. The probability of being fined increases in f because it is easier for a regulator to prove fraud in court when the firm is committing more fraud. If the regulator successfully proves that the firm defrauded a consumer, it sets the fine as the cost to the firm of producing the real product, c^h. This fine is meant to mimic a regulator requiring the company to provide the high quality product to the consumer if caught.

The firm first solves for the optimal price, which is a constant markup over its marginal cost:

$$p_{ij} = \frac{\sigma}{\sigma - 1}[(1 - f_{ij})c_i^h + f_{ij}c_i^l + f_{ij}(d_i f_{ij})c_i^h]\tau_{ij} \tag{5}$$

2.3 Fraud Rate

The firm cannot commit to its probability of f_{ij} when setting a price and agreeing to sell quantity. This lack of commitment is meant to capture the lack of enforceability of contracts across countries. Thus, after setting its price and agreeing to ship q_{ij}, the firm maximizes its profits subject to f_{ij}, holding p_{ij} and q_{ij} constant:

$$\max_{f_{ij}}(p_{ij} - (1 - f_{ij})c_i^h\tau_{ij} - f_{ij}c_i^l\tau_{ij} - f_{ij}(d_i f_{ij})c_i^h\tau_{ij})q_{ij} \tag{6}$$

The optimal f_{ij}^* does not vary by destination country (i.e. $f_{ij}^* = f_i^*$) and is:

$$f_i^* = \frac{1}{2d_i}(1 - c_i^l/c_i^h) \tag{7}$$

The fraud rate f_i^* is thus decreasing in the likelihood of enforcement d and in the relative cost of fraud c^l/c^h. Because the fraud rate does not vary by destination country, the price p_{ij} only varies across destination countries due to the iceberg trade cost τ_{ij}.

2.4 Gravity Equation

We then show that gravity holds for fraud complaints. The key assumption is that complaints from consumers in country j are proportional to fraud at rate β_j; that is, not all harmed consumers complain, but complaining is independent of the location of the firm causing fraud. This assumption would be violated if, for example, American consumers were more likely to complain about American companies knowing that enforcement is more likely if the scammers are domestic than if they are abroad. In general, the realism of this assumption will depend upon the reasons for complaining – such as an expectation for recovery of losses compared to preventing future harm to others – as well as whether consumers complain to a government agency that might only be able to recover losses domestically or a money transfer network where recovery might depend less on location.

Given this assumption, trade volume $p_{ij}q_{ij}$ and complaint volume, $\beta_j f_i p_{ij} q_{ij}$, (both from consumers in country j for firms in country i) are:

$$p_{ij}q_{ij} = X_{ij} \quad = \quad a_{ij}\tau_{ij}^{-\sigma}(\frac{Y_i}{\Pi_i^{1-\sigma}})\frac{E_j}{P_j^{1-\sigma}} \tag{8}$$

$$\beta_j f_i p_{ij} q_{ij} = C_{ij} \quad = \quad a_{ij}\tau_{ij}^{-\sigma}(f_i\frac{Y_i}{\Pi_i^{1-\sigma}})\beta_j\frac{E_j}{P_j^{1-\sigma}} \tag{9}$$

where P_j is the price index for country j and Π_i is a multilateral resistance term.[12]

The complaint volume between countries can be decomposed into four terms:

1. A gravity term $\tau_{ij}^{-\sigma}$ that depends upon the distance between countries τ_{ij}.

2. A destination fixed effect $\beta_j \frac{E_j}{P_j^{1-\sigma}}$ that depends upon the selection probability of complaining β_i, the expenditure of country j E_j, and country j's price index P_j.

3. A origin fixed effect $f_i \frac{Y_i}{\Pi_i^{1-\sigma}}$ that depends upon the probability of fraud in country i f_i, the production of country i Y_i, and country i's multilateral resistance term Π_i.

4. An idiosyncratic taste shock a_{ij}.

The gravity model for trade volumes is the same as for complaints, except that the destination fixed effect is $\frac{E_j}{P_j^{1-\sigma}}$ and so does not include the selection probability of complaining β_i, and the origin fixed effect $\frac{Y_i}{\Pi_i^{1-\sigma}}$ does not include the probability of fraud in country i f_i. Thus, if we take logs and define the origin fixed effect for complaints and trade volumes as γ_i^C and γ_i^T, we can identify the fraud rate in country i from the difference between the origin fixed effect for complaints and the origin fixed effect for trade volume:

$$\log f_i = \log(f_i \frac{Y_i}{\Pi_i^{1-\sigma}}) - \log(\frac{Y_i}{\Pi_i^{1-\sigma}}) = \gamma_i^C - \gamma_i^T \tag{10}$$

We use this relationship to estimate a country specific fraud rate in Section 4.

[12]These are defined by:

$$\begin{aligned} \Pi_i^{1-\sigma} &= \sum_j a_{ij} P_j^{\sigma-1} \tau_{ij}^{-\sigma} E_j \\ P_j^{1-\sigma} &= \sum_i a_{ij} \Pi_i^{\sigma-1} \tau_{ij}^{-\sigma} Y_i \end{aligned}$$

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3 Gravity

3.1 Empirical Specification

The empirical gravity model we estimate follows the standard approach in the literature. Because we do not have access to a long time series, we first collapse our data to a cross-sectional dataset of country-country pairs, with the key outcome being the sum of complaints from one country to the other throughout the time period.

We then reframe equation (8) and equation (9) in log form, where C_{ij} is the complaint volume from consumers in j about firms in i, and X_{ij} is the trade volume:

$$\log E[C_{ij}] = \beta^C \log t_{ij} + \gamma_i^C + \delta_j^C + u_{ij}^C \tag{11}$$

$$\log E[X_{ij}] = \beta^T \log t_{ij} + \gamma_i^T + \delta_j^T + u_{ij}^T \tag{12}$$

Each specification includes origin fixed effects γ_i and destination fixed effects δ_j. As discussed in Section 2.4, γ_i^C captures several factors including country i's production, a multilateral resistance term, and the fraud rate in country i. Similarly, δ_j^C captures country j's expenditure, its price index, and its rate of complaining. We return to an explicit investigation of patterns in these fixed effects in Section 4.

The term t_{ij} is the empirical counterpart of the iceberg trade costs τ_{ij}, and includes several measures of geographic and cultural proximity. We use data on country characteristics and relationships between countries from the United States International Trade Commission Dynamic Gravity Dataset.[13] In particular, we include the geographic distance, together with dummies for whether the countries share a border, whether one country was ever a colony of the other, and whether they share a common language.[14] We also include a measure of

[13]See Gurevich and Herman (2018) for an in-depth description of the dataset construction and the various measures included in the data.

[14]The distance measure is calculated, following the methodology developed by Mayer and Zignago (2011), based on the distance in kilometers between pairs of cities, weighted by the proportion of the country's population residing in each city. Because the distace measure is constructed in this way, it allows us to

intra-national distance, which is standard in the literature.[15] We limit the data to 2014 to 2021, the period for which we also have complaints from Consumer Sentinel.

In addition, in some specifications we include two additional terms. First, we sometimes include a set of indicators for whether the countries had any active trade agreements at any point within the study period, including preferential trade agreements, customs unions, free trade agreements, and partial scope agreements. These terms allow complaint and trade flows to be affected by the existence and type of trade agreements. Second, we sometimes include a dummy variable for complaints or trade within the same country. This term captures potential home bias – a greater propensity to consume local goods.[16]

For data on trade, we use trade information from the ITC's International Trade and Production Database for Estimation (Borchert et al., 2020) that provides pairwise measures of trade by industry for the years 2000-2016. We collapse this dataset for the years since 2014 over all industries. We also separately measure trade in services for robustness exercises.

Our empirical approach estimates equation (11) using Poisson Pseudo Maximum Likelihood (PPML), primarily to account for flows with no complaints between countries, which would be dropped in the log expressions. PPML also has the added benefit that it accounts for heteroscedasticity (Silva and Tenreyro, 2006) and produces consistent fixed effects (Fally, 2015).

3.2 Estimates

Panel A of Table 5 shows the estimates of the gravity equation for consumer complaints in Consumer Sentinel. We display four specifications. The first column includes only distance

use intra-national distance in specifications where we include same-country pairs. For more information see Gurevich and Herman (2018).

[15]The inclusion of intra-national distance is important, among several reasons, to remain consistent with the theoretical model where consumers choose between domestic and international products (Yotov et al., 2016). In the canonical trade model it also serves to consistently identify the effects of various trade policies. Intra-national distance is calculated in the same way as international distance, as the population-weighted kilometer distance between cities.

[16]See McCallum (1995), Obstfeld and Rogoff (2000), Wolf (2000) and Yi (2010) for examples of home bias.

measures, company country fixed effects, and consumer country fixed effects. The second column adds controls for trade agreements. The third and fourth columns account for differences for same country pairs in different ways; the third column includes a dummy for same country pair while the fourth column excludes same country pairs and so limits the sample to only international complaints.

Across all specifications, we find a strong negative link between the number of complaints and the distance that separates the two countries. A 10% increase in international distance decreases the number of complaints by 4 to 5% across specifications. The effect of intranational distance is smaller, with a 10% increase in intranational distance decreasing the number of complaints by 1.5 to 2%.

Whether the countries share a common language also has a strong positive effect on the number of complaints. Countries that share the same language have 80% to 105% greater complaint volume between them. In contrast, we do not find significantly greater complaint volume between a colonizer and former colonies. After including trade agreement controls, we do not find that contiguity matters for complaint volume either.

We then compare gravity estimates for complaint volume to estimates for trade volume reported in Panel B. While distance has a negative effect in both models, it has a smaller effect on complaint volume than it does on trade volume. A 10% increase in international distance decreases trade volume by 7 to 8%, compared to 4 to 5% for complaint volume. On the other hand, a common language predicts trade volume less than it does complaint volume, with a 20% to 40% increase in trade volume with a common language compared to a 80% to 105% increase for complaints.[17] Unlike for complaints, contiguity matters for trade volume, with a 25 to 65% increase in trade volume for contiguous countries.[18]

We next examine heterogeneity in the source of the complaints. Table 6 shows the

[17] In the ITC Dynamic Gravity Dataset, countries are considered as sharing a common language if they share an official language or languages that are "commonly spoken" according to the CIA World Factbook.

[18] As a robustness exercise, Table A6 estimates the trade gravity model only including non-zero trade flows for country pairs with non-zero flows of complaints. The results are quite similar. As another robustness check, Table A7 uses data only for trade in services, rather than all types of goods. Here again the results are quite similar.

Table 5: Gravity Estimates

	(1)	(2)	(3)	(4)
A. Complaints				
ln(International Distance)	-0.475***	-0.455***	-0.426***	-0.404***
	(0.0402)	(0.0402)	(0.0486)	(0.0439)
ln(Intranational Distance)	-0.183***	-0.159**	-0.172**	
	(0.0538)	(0.0528)	(0.0666)	
Common Language	0.608***	0.621***	0.616***	0.713***
	(0.0916)	(0.0853)	(0.0879)	(0.0954)
Contiguity	-0.514***	-0.0808	-0.0528	0.0337
	(0.117)	(0.0990)	(0.106)	(0.107)
Colony	0.173	0.190	0.205	-0.248**
	(0.116)	(0.114)	(0.111)	(0.0936)
Same-Country Pair			0.366	
			(0.662)	
N	63448	63448	63448	63196
B. Trade Volume				
ln(International Distance)	-0.719***	-0.757***	-0.746***	-0.706***
	(0.0465)	(0.0451)	(0.0697)	(0.0314)
ln(Intranational Distance)	-0.315***	-0.373***	-0.376***	
	(0.0675)	(0.0665)	(0.0715)	
Common Language	0.333***	0.242**	0.241**	0.200***
	(0.0780)	(0.0813)	(0.0810)	(0.0543)
Contiguity	0.282**	0.482***	0.492***	0.224***
	(0.108)	(0.0887)	(0.0974)	(0.0575)
Colony	0.234	0.181	0.185	0.0972
	(0.134)	(0.127)	(0.123)	(0.0655)
Same-Country Pair			0.123	
			(0.643)	
N	63448	63448	63448	63196
Company Country FE	X	X	X	X
Consumer Country FE	X	X	X	X
Trade Agreement Controls		X	X	
Same-country pairs omitted				X

Notes. Table shows estimates of equation (11) and equation (12). The dependent variable in panel A is the number of complaints from consumers in country i about companies in country j, using data from Consumer Sentinel from 2014-2021 across all sources. The dependent variable in panel B is the trade volume across all industries from the ITC International Trade and Production Database, in real dollars. International and intranational distance are calculated as population-weighted distances in kilometers across main cities. Trade controls include separate dummies for whether the two countries had engaged in preferential trade agreements, at least one customs union, economic integration agreements, free trade agreements, and partial scope agreements at any point between 2014-2021. Model is estimated using Poisson Pseudo Maximum Likelihood. 56 of the possible 63,504 pairs are excluded due to missing control variables. Robust standard errors. $*p < 0.05, **p < 0.01, ***p < 0.001$

gravity estimates for the two other data sources: MT and the ACCC. The key use of the MT data is that we do not have to rely on consumers recording the country of the company that defrauded them. The first column of the table shows that MT complaints also exhibit gravity, with larger estimates than in the Consumer Sentinel data. Increasing physical distance by 10% decreases complaint volumes by 7.2%, and sharing a common language increases complaint volumes by 218%. An additional benefit of the MT data is that we can observe the amount of money that was wired through the transaction: this information is not reliable across all complaints in Consumer Sentinel. Column 2 examines the dollar volume of transfers for MT. The coefficients are quite similar using either dollar values or the number of complaints.

The final column of the table shows the same exercise using data from Australia-based country pairs in the ACCC data. The benefit of this data source is that it is not US-based. Because all the data include Australian consumers or companies, the only coefficient of interest is the international distance, which is almost identical to that in MT at a 7.0% reduction in complaints with a 10% increase in distance.[19] Table A3 provides a similar table examining subsets of the Consumer Sentinel data.[20]

As an additional source of heterogeneity we grouped complaints in the Consumer Sentinel and MT data by the content of the product that the consumers bought. Table A4 and Table A5 show these results for the five categories of complaints in each dataset with the most international complaints. Overall, the general result holds: complaints in most types of frauds and scams display evidence of gravity. Nevertheless, there are some differences. In both datasets, lottery and prize scams exhibited the most gravity. Other types of scams, such as online shopping and imposter scams, exhibited a smaller relationship between distance and complaints. In the MT data, two categories of scams, prepayment and relationship

[19] The common language flag becomes a flag for English speaking countries, and the colony flag only identifies the United Kingdom and a small number of Pacific Islands. The contiguity flag drops out altogether.

[20] The largest sources of international complaints in the Consumer Sentinel database are reported to the FTC and its econsumer.gov website and money transfer companies like MoneyGram and Western Union. We also investigate the cyber crime agencies, which unsurprisingly show less evidence of gravity.

Table 6: Heterogeneity in Gravity Results by Data Source

	(1) MT (N)	(2) MT ($)	(3) ACCC
ln(International Distance)	-0.722***	-0.710***	-0.703***
	(0.0882)	(0.0949)	(0.00477)
ln(Intranational Distance)	-0.290	-0.0234	-5.614***
	(0.201)	(0.189)	(0.00692)
Common Language	1.158***	0.973***	-0.101***
	(0.149)	(0.146)	(0.00813)
Contiguity	-0.218	-0.112	
	(0.173)	(0.172)	
Colony	0.297	0.144	-1.149***
	(0.164)	(0.157)	(0.0227)
Same-Country Pair	-2.589	-4.364**	
	(1.625)	(1.537)	
N	63448	63448	63448
Company Country FE	X	X	X
Consumer Country FE	X	X	X
Trade Agreement Controls	X	X	X

Notes. Table shows estimates of equation (11) separately by the source of data. The dependent variable is the number of complaints from consumers in country i about companies in country j, using the specified data source. Columns 1 and 2 include data from MT for 2004 to 2014. Column 2 includes sum of the dollar value of the wired funds related to the complaint, rather than the count of complaints. Column 3 uses complaints filed with the ACCC. International and intranational distance are calculated as population-weighted distances in kilometers across main cities. Trade controls include separate dummies for whether the two countries had engaged in preferential trade agreements, at least one customs union, economic integration agreements, free trade agreements, and partial scope agreements at any point between 2014-2021. Model is estimated using Poisson Pseudo Maximum Likelihood. 56 of the possible 63,504 pairs are excluded due to missing control variables. Robust standard errors.
$*p < 0.05, **p < 0.01, ***p < 0.001$

scams, even had small coefficients that were not statistically significant. These two types of scams were much more likely to occur between countries with similar languages, likely because of the repeat interactions needed to complete the scam.

4 Estimated Fraud Rates

4.1 Ranking Countries by Estimated Fraud Rates

We then use the gravity estimates from the previous section to measure fraud rates across countries. As described in Section 2.4 and shown in equation (10), the theoretical framework implies that the fraud rate for a country is the difference in the origin fixed effect in the complaints gravity equation and origin fixed effect in the trade volume gravity equation. For ease of interpretability, we standardize the resulting estimated fraud rates to have mean zero and standard deviation of one. Thus, a fraud rate of 0.5 is 0.5 standard deviations above the global average.

Figure 1 depicts a heat map of estimated fraud rates across the world using the Consumer Sentinel dataset, colored by quantiles of the distribution.[21] Darker shaded countries have higher estimated fraud rates. To summarize the differences in regional patterns across the three data sources, the upper left figure of Figure 4 displays the population-weighted mean fraud rates by different world regions for the Consumer Sentinel data.

Countries with the highest fraud rates are quite different than the countries with the most fraud complaints shown earlier in Table 4. For example, Western European countries, which have a large number of complaints in the data, do not appear to have high fraud rates; the European average is -0.43. Instead, the regions with the highest fraud rates are those that are in close proximity to the United States; the Caribbean, at 1.58, North America, at 0.98, and Central America, at 0.37. Because small islands in the Caribbean or Central America are not clearly visible in the world map, Figure A5 shows the estimated fraud rates for just these two regions. Jamaica, for example, has an estimated fraud rate of 3.43 standard deviations. Several other smaller Caribbean nations, such as Dominica, Anguilla, and the Turks and Caicos, have similarly large fraud rates. In Central America, the highest estimated fraud rate belongs to Belize, though Nicaragua and Panama also have relatively high rates.

The United States and Canada also have high fraud rates, at 1.56 for the US and 1.45 for Canada. In fact, the United States has the 14th highest estimated fraud rate in the world. As we discuss below, however, we believe that the fraud rate for these two countries is still

[21] Our preferred specification controls for distance and trade frictions, as well as a same-country pair flag, but does not omit the same-country pairs. It corresponds to Column 3 in Table 5. The correlation between the estimated fraud rates from the various specifications is very high, above 0.95, and the resulting rankings are almost identical.

somewhat inflated because of the US- and Canada-biased reporting in the main data sources of Consumer Sentinel.

In addition, Figure 1 shows that several countries in West Africa have high estimated fraud rates. Ghana, Benin, and Gambia are among the countries with the highest fraud rates in the world. Nigeria, which exemplifies the fraud schemes this area of the world is notorious far, is not among the area's worst offenders, however. The rest of Africa does not have particularly high fraud rates; on average, Africa as a whole is slightly above the global average.

Although not as striking as the hotspots in West Africa and the Caribbean, there are also high fraud countries in Asia. China has an estimated fraud rate of 0.11, and other smaller nations in the region, such as the Philippines, Hong Kong, and Singapore, have higher rates. East Asia and South Asia are slightly above the global average at 0.22 and 0.08, while Southeast Asia is below the global average at -0.32. Finally, countries that have experienced recent violent conflict seem to have higher estimated fraud rates, such as Afghanistan, Yemen, Syria, and Ukraine.

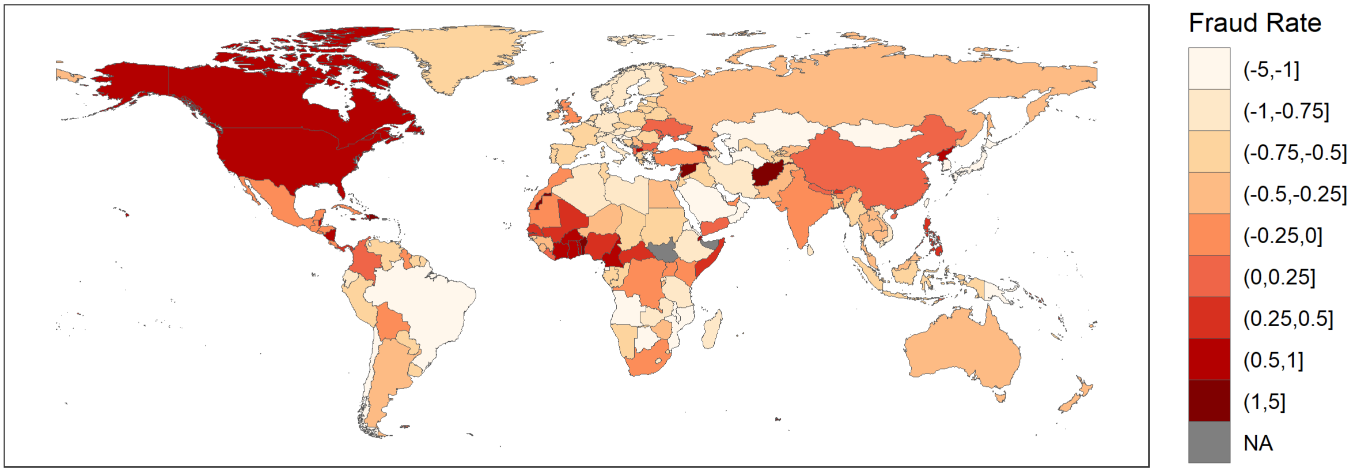
Table A8 lists the 25 countries with the highest estimated fraud rates.[22]

The identifying assumption behind our estimated fraud rates is that victimized consumers in a given country are equally likely to complain, regardless of where the company that victimized them is located. However, as noted earlier, many of the complaints to Consumer Sentinel are to consumer protection authorities in the US and Canada, so consumers might be more likely to complain about companies based in North America.

To alleviate this issue, we examine only complaints from MT and from the ACCC. MT is a money transfer company and not a US governmental agency, and so may have less of a bias towards North American companies based on differential complaining. In addition, the MT data has higher quality company location information since location is determined

[22]We limited this list to just countries that had population above 500,000 in the study period. This limitation primarily excludes small Caribbean nations. Table A9 shows the full set of countries, normalizing using the mean and standard deviation for the full set of countries.

Figure 1: Estimated Fraud Rates, All Consumer Sentinel Sources



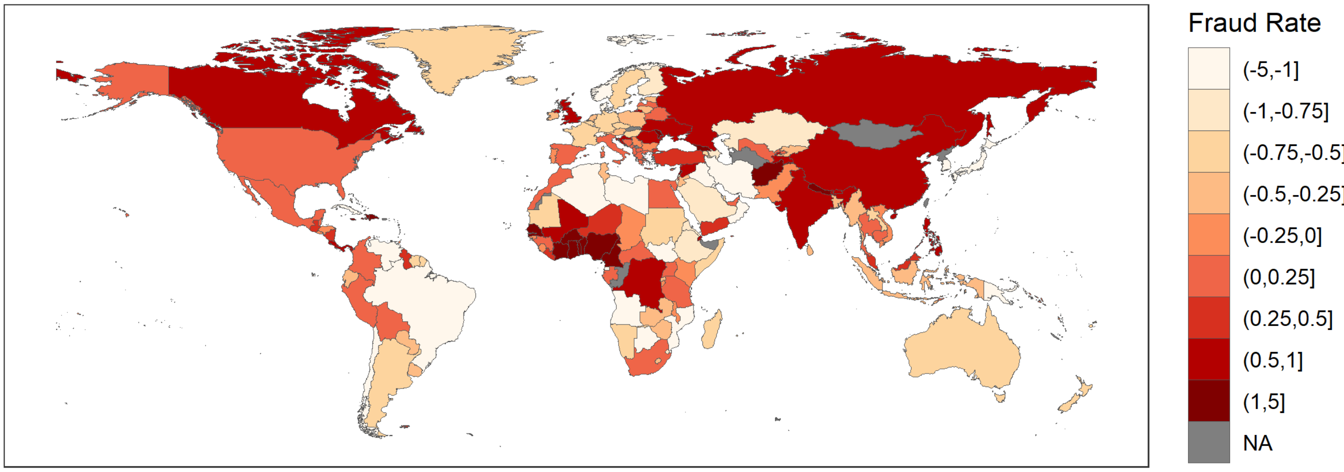
Notes. Map shows estimated fraud rates by country. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution.

by the destination of the money transfer rather than consumer recall. Figure 2 depicts a heat map of estimated fraud rates based on these MT money transfer complaints alone. In the Appendix, Table A10 shows the names of the countries with the highest estimated fraud rates using the MT data. As predicted, the United States and Canada have lower estimated fraud rates here than with the overall data; the average for North America is 0.58 compared to 0.98 for the full Sentinel data. However, the main regional patterns remain. West Africa and the Caribbean, in particular, have high rates of fraud. Also notable is that the money transfer complaints show higher rates of fraud in Russia, China, and India.[23]

We also used data from the ACCC, which is more limited in the number of country pairs it contains but, because it focuses on Australian consumers and companies, is not subject to potential concerns about US bias. Figure 3 shows these regional patterns. Australia itself has by far the highest fraud rate according to these estimates, though this should be

[23] As a further check, we used data on money transfer companies from Consumer Sentinel, with results shown in Figure A7.

Figure 2: Estimated Fraud Rates, MT Data



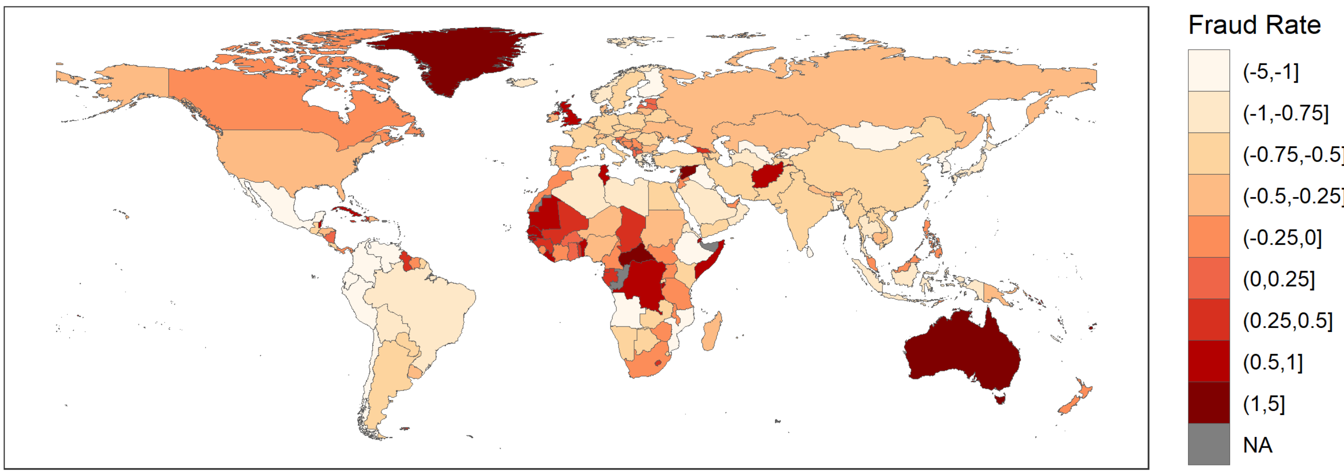
Notes. Map shows estimated fraud rates by country, limited to MT data only. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution when including all Consumer Sentinel sources.

interpreted with caution because all of the complaints either originate in Australia or are about entities claiming to be Australian. The familiar trends in high fraud rates in Western African countries persists, however, as does the higher rates of fraud in countries, like Syria and Afghanistan, with active military conflicts. Not visible in the map is that the Caribbean also ranks high in these fraud rates. The map does show, however, that the United States and Canada are not persistent sources of high volumes of fraud complaints: both are below average among ACCC complaints. Table A11 shows the 25 countries with the highest fraud rates in the ACCC data.

Figure 4 displays the population-weighted mean fraud rates by different world regions defined in the ITC data for all three datasets.[24] This figure helps to systematically compare patterns in fraud rates. Overall, the rankings are quite similar, especially when comparing the Consumer Sentinel and MT data, with the highest rates in the Caribbean. All the

[24] Australia, which has a fraud rate of 60 standard deviations above the mean in the ACCC data, was omitted in the ACCC estimates.

Figure 3: Estimated Fraud Rates, ACCC



Notes. Map shows estimated fraud rates by country, limited to ACCC data only. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution when including all Consumer Sentinel sources.

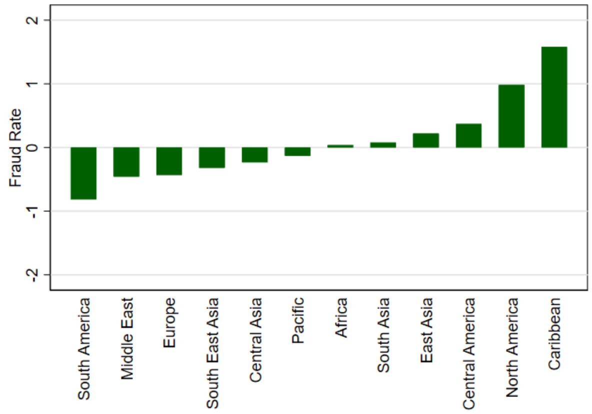
data sources also have low rates in South America and the Middle East. Figure A11 shows comparable bar graphs for subsets of the Consumer Sentinel Data.

The Appendix includes additional lists of countries with the highest fraud rates based on different specifications and datasets. Table A12 limits the Consumer Sentinel data to just the two money transfer companies.Table A13 and Table A14 limit complaints to just those for online shopping for the Consumer Sentinel and MT data, respectively.[25] Table A15 uses Consumer Sentinel data, but relative to trade in services rather than all industries.

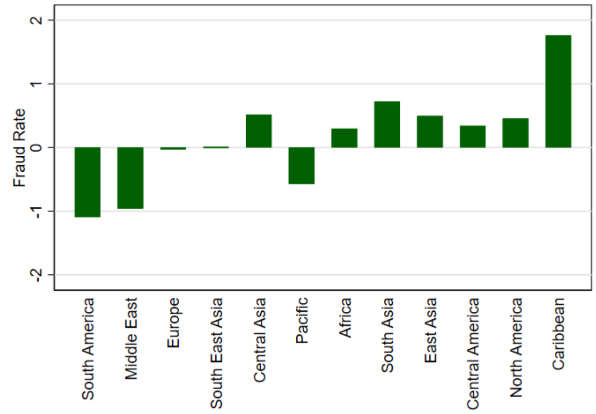
We examine the analogous country-level complaint rates, based on the difference in the destination fixed effect, in Appendix A1. Our highest country-level complaint rates are for the US and Canada, with high rates of complaints from Australia and New Zealand as well. Countries in East Asia in particular have much lower rates of complaints into Consumer Sentinel.

[25]Figure A8 and Figure A9 show the related maps.

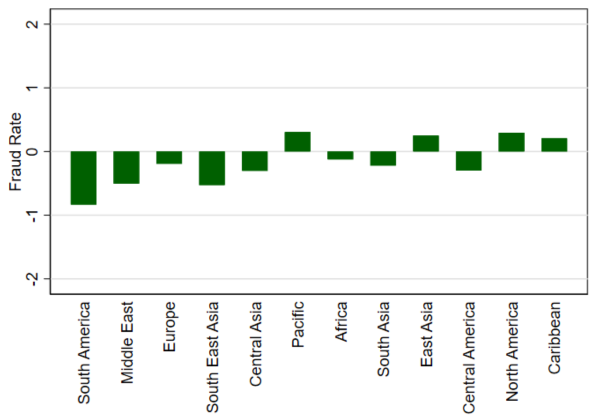
Figure 4: Estimated Fraud Rates, by Region



a) Consumer Sentinel



b) MT Data



c) ACCC

Notes. Figure shows population-weighted mean fraud rates by region. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Regions groupings come from the ITC Dynamic Gravity Dataset, with Eurasia combined with Central Asia.

4.2 What Predicts Estimated Fraud Rates?

As Figure 1 shows, certain countries seem to have very high rates of fraud. In the model in Section 2.3, the level of fraud decreases with a greater detection probability of fraud and with a greater relative cost of committing fraud.

We proxy for the relative cost of fraud by per-capita GDP, which we view as a proxy for a country's productivity; high productivity countries would find it cheaper to produce the high quality good of the model, and so the relative cost of fraud is higher for them. The first panel of Table 7 shows a large and negative relationship between the country fraud rates and GDP per capita; a 100% increase in GDP per capita is associated with a 0.25 to 0.35 standard deviation decrease in the fraud rate.

In order to proxy for the detection probability, we relate the estimated fraud rates to different country-level measures of governance. We are particularly interested in how government policy related to the types of behaviors that consumers complain about—fraud and scams—might be related to resulting complaints. We rely on the Worldwide Governance Indicators (WGI), which create annual scores (standardized to mean zero and standard deviation 1) for each country on three dimensions of governance from 1996-2019 (Kaufmann, Kraay and Mastruzzi, 2010). We take the mean of each measure for each country for the relevant time period (i.e. since 2014).[26]

We use three of the six indicators in this study. The rule of law measure describes the extent to which a country's inhabitants have confidence and abide by the society's rules, as well as the extent of crime of different types. The government effectiveness measure summarizes the quality of public and civil services within the country, and the credibility and independence of the government. Finally, the regulatory quality measure summarizes a country's ability to regulate and promote private sector development, and seems particularly relevant in the context of fraud: a primary purpose of government regulatory agencies is to stymie these types of crimes. Three additional measures are included in the WGI but do not seem as relevant to our particular research question – voice and accountability, political stability and absence of violence, and control of corruption. We calculate each country's mean score across the three measures to create a population-weighted mean "governance index."

The second panel of Table 7 shows a negative relationship between the governance index and the country fraud rates, with a one standard deviation increase in the governance

[26] Table A16 shows the relationship between the fraud rates and the individual components of the index.

index associated with a decrease in the fraud rate by 0.1 to 0.3 standard deviations across specifications. The relationship is weaker than for GDP per capita, and is not statistically significant for the ACCC. However, when we include the governance index along with log GDP per capita we find a strong negative relationship for GDP per capita but positive and statistically insignificant for the governance index. This insignificance is likely due to multicollinearity, with a 0.79 correlation between the two measures. Still, we interpret these results as evidence of lower fraud rates in wealthier countries and, to a lesser extent, countries with more robust governing institutions.

Table 7: Fraud Rates and Country Characteristics

	(1) CS	(2) WU	(3) ACCC
Log GDP per capita	-0.263***	-0.339***	-0.246***
	(0.0604)	(0.0615)	(0.0575)
r2	0.0992	0.155	0.0870
N	176	167	174
Governance Index	-0.162*	-0.290***	-0.103
	(0.0708)	(0.0797)	(0.0747)
r2	0.0245	0.0765	0.00948
N	176	167	174
Log GDP per capita	-0.398***	-0.391***	-0.421***
	(0.109)	(0.112)	(0.0954)
Governance Index	0.218	0.0844	0.290*
	(0.120)	(0.134)	(0.115)
r2	0.113	0.154	0.113
N	174	166	172

Notes. Table shows estimates regressions of country-level estimated complaint rates on country characteristics. GDP and population come from the US ITC gravity dataset. Other country characteristics come from the WGI. Robust standard errors. $*p < 0.05, **p < 0.01, ***p < 0.001$

5 Conclusion

In this paper, we provide a detailed look at the sources of international fraud by analyzing a wealth of information on individual fraud complaints within a framework based in economic theory. We adapt the well-studied Armington model of trade and show that, subject to some modest assumptions, the flow of fraud across borders follows a gravity model, like trade flows. We use this insight to empirically estimate the gravity model, as well as to identify countries that have rates of fraud that are disproportionately high or low relative to their exports, conditional on the various controls in the gravity estimation. This “Fraud Index” is the first of its kind, and is potentially useful for policymakers and others interested in worldwide variation in fraud rates.

We find that fraud flows do follow a gravity model. However, geographic proximity, such as distance and contiguity, are less important for fraud than for trade, and cultural proximity is more important. These differences likely reflect the fact that fraudulent transactions increasingly happen online or through voice over internet protocol (VOIP) services. We also document geographic clusters of high-fraud countries. The Caribbean and West Africa, in particular, have high rates of fraud. In addition, high rates of fraud are more likely in less wealthy countries, as well as countries with less developed regulatory institutions.

For future research, it would be helpful to examine the effects of interventions to reduce cross-border fraud, such as the FTC’s lawsuits against money transfer companies or law enforcement collaborations between different countries. Second, the way that consumers pay for fraudulent transactions may change in the future, such as using Bitcoin or other cryptocurrencies. Researchers could thus examine public data on cryptocurrency ledgers to see how our model fits likely fraudulent crypto transactions. Finally, our data reflects the issues of consumers who choose to complain, who are mostly located in Western countries. Future work could examine how consumers on the margin of complaining differ from inframarginal consumers (Grosz and Raval, 2022), or the issues of consumers in East Asia or other locations less likely to complain to our data sources.

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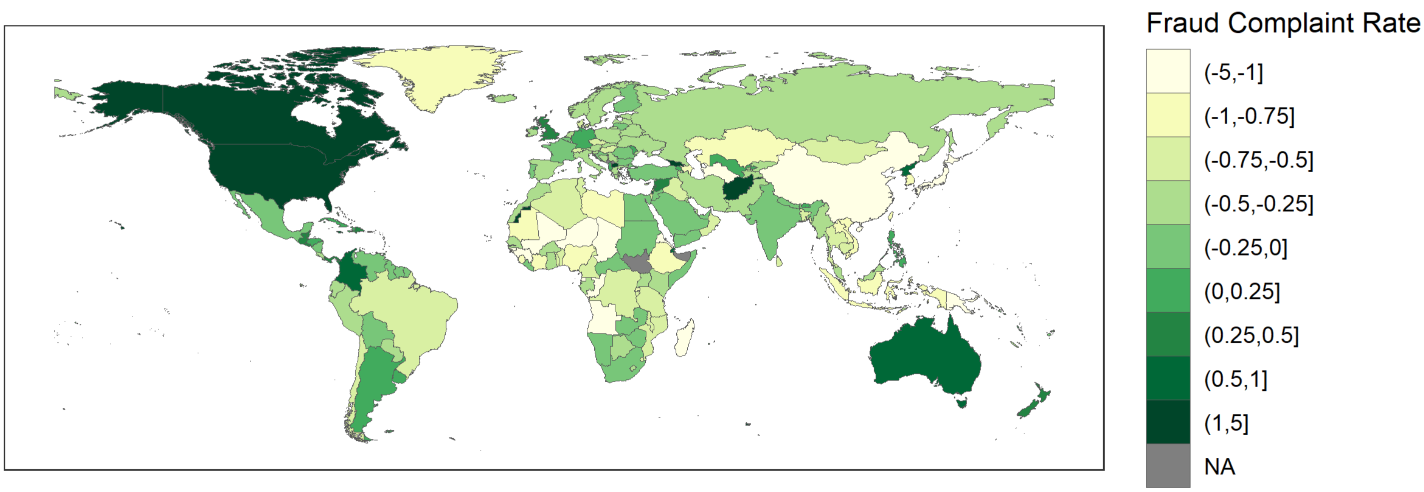
A1 Which countries complain?

The results of the gravity estimation can also tell us which countries are more likely to complain for each dataset. We calculate this "complaint rate" in a manner parallel to the fraud rate itself. In the context of the model described in Section 2.4, we can identify the fraud complaint rate in country j as the difference between the destination fixed effects for complaints and destination fixed effects for trade volume, which we designate as δ_j^C and δ_j^T, respectively:

$$\log \beta_j = \log(\beta_j \frac{E_j}{P_j^{1-\sigma}}) - \log(\frac{E_j}{P_j^{1-\sigma}}) = \delta_j^C - \delta_j^T \tag{13}$$

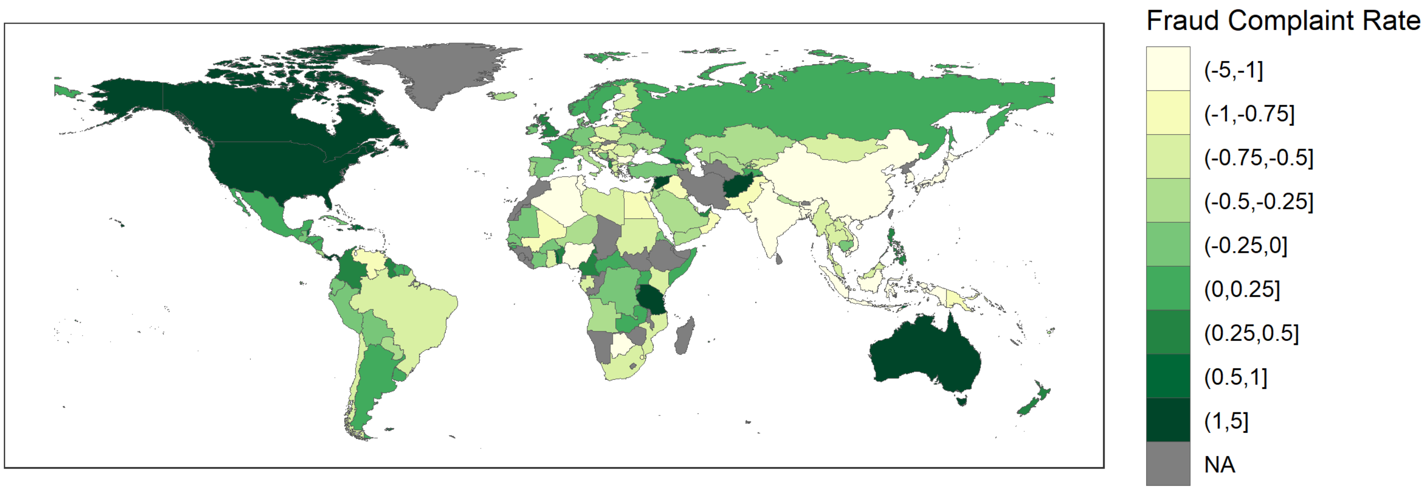
Figure A1 shows the estimated complaint rates using the Consumer Sentinel data. Figure A2 shows the same map using data from a large money transfer company. As with the estimated fraud rate, there are some clear regional patterns. More affluent countries, such as in North America, Northern Europe, Australia, and New Zealand, have higher complaint rates. In addition, a few countries have high complaint rates and high fraud rates, such as the Philippines and several of the Caribbean nations. Figure A2 and Figure A3 show similar analyses using the MT and ACCC data, respectively. Figure A4 summarizes the individual complaint rates by region.

Figure A1: Estimated Complaint Rates, All Consumer Sentinel Sources



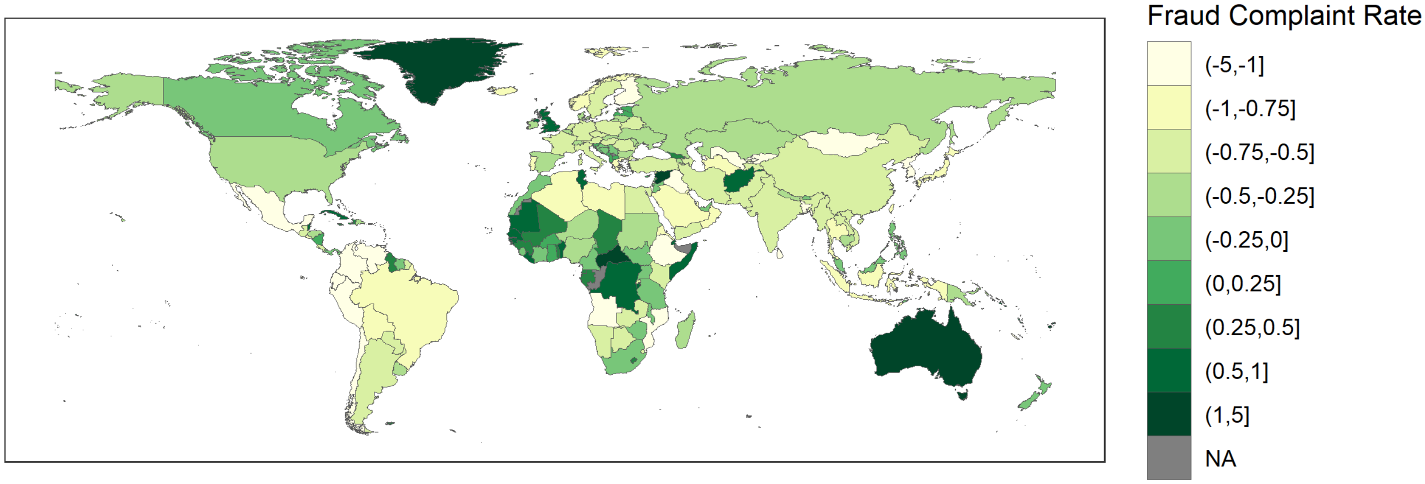
Notes. Map shows estimated fraud complaint rates by country. Estimated fraud complaints rates are the difference between the consumer fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution of fraud rates using the company fixed effects.

Figure A2: Estimated Fraud Complaint Rates, MT Data



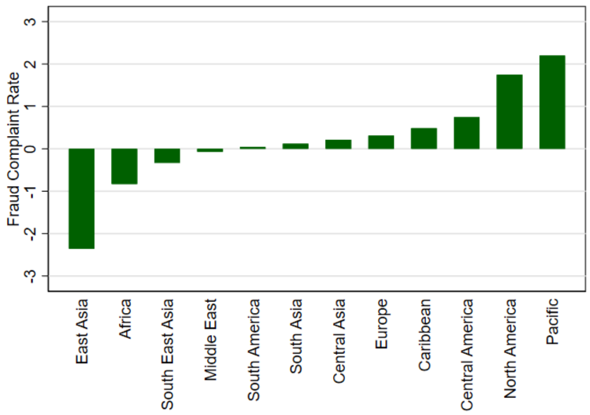
Notes. Map shows estimated fraud complaint rates by country, using complaints from a large money transfer company. Estimated fraud complaints rates are the difference between the consumer fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution of fraud rates using the company fixed effects.

Figure A3: Estimated Fraud Complaint Rates, ACCC

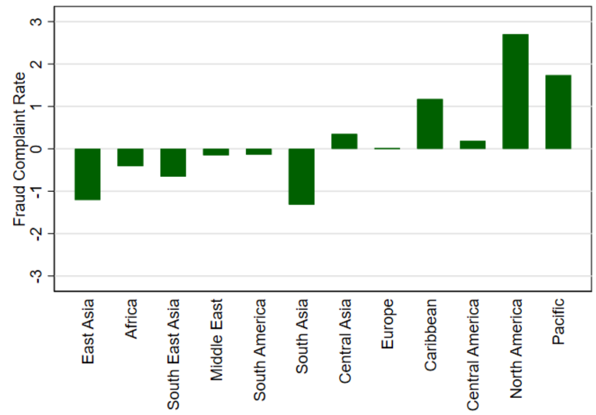


Notes. Map shows estimated fraud complaint rates by country, using complaints in the ACCC data. Estimated fraud complaints rates are the difference between the consumer fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution of fraud rates using the company fixed effects.

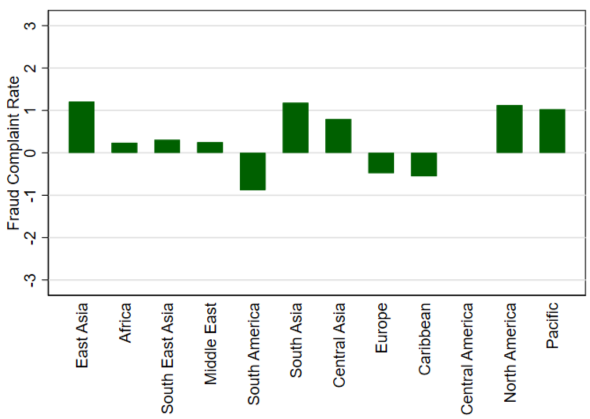
Figure A4: Estimated Fraud Complaint Rates, by Region



a) Consumer Sentinel



b) MT Data

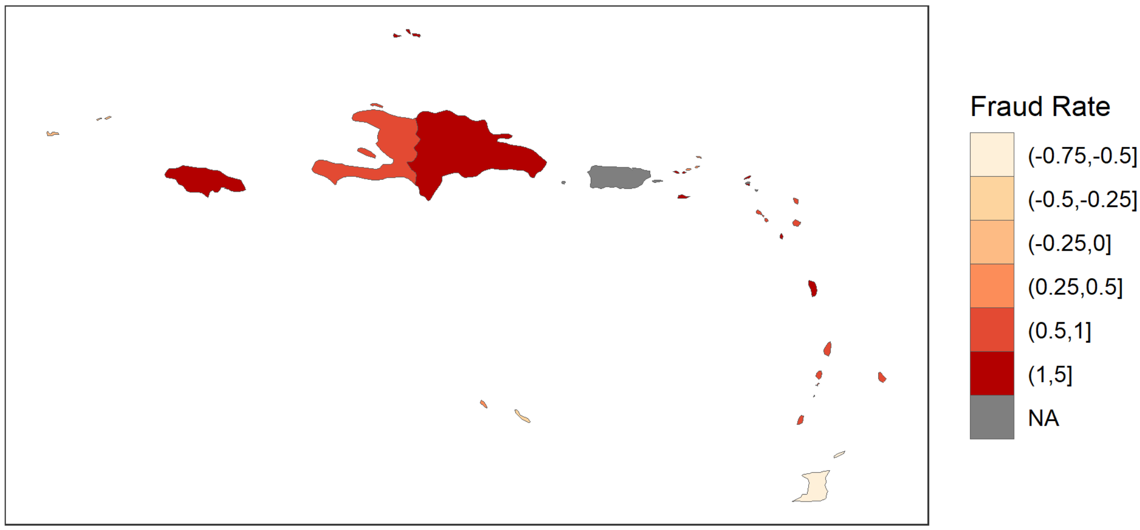


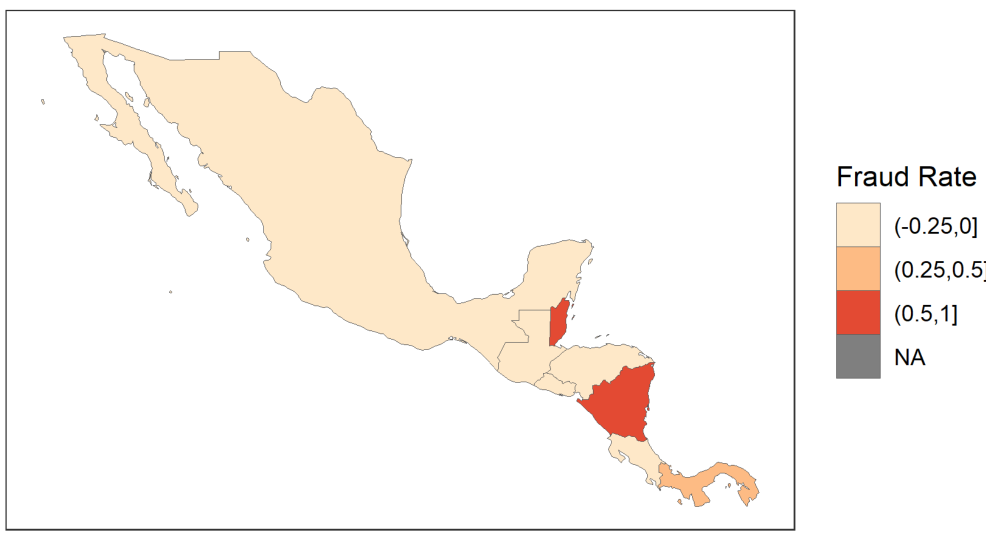
c) ACCC

Notes. Figure shows population-weighted mean fraud rates by region. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Regions groupings come from the ITC Dynamic Gravity Dataset, with Eurasia combined with Central Asia.

A2 Appendix Tables and Figures

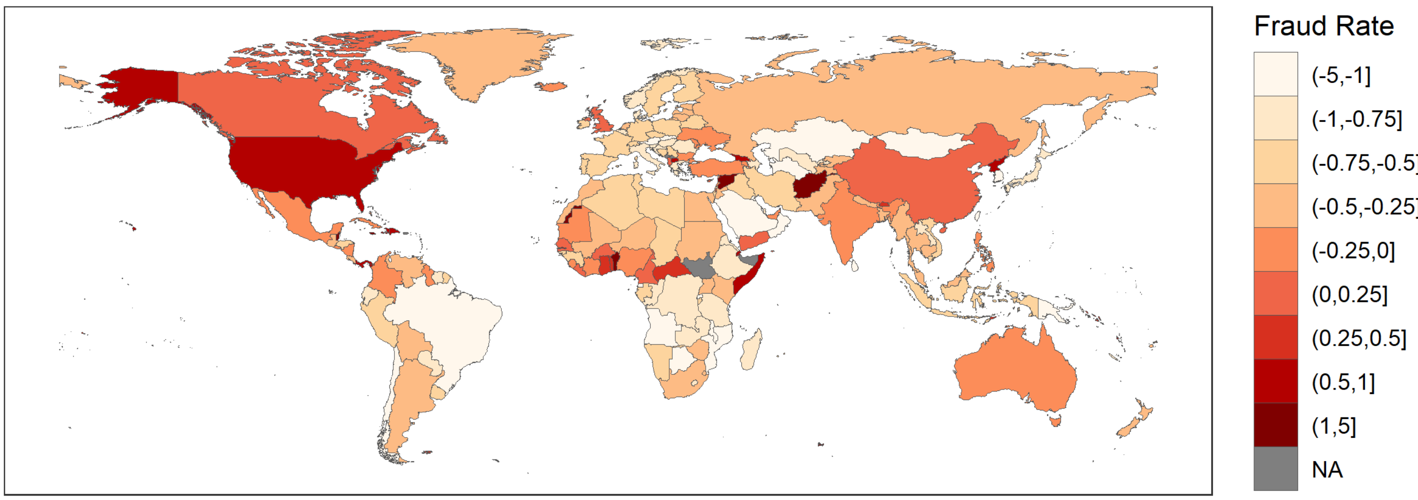
Figure A5: Estimated Fraud Rates, All Consumer Sentinel Sources, Caribbean and Central America Closeup





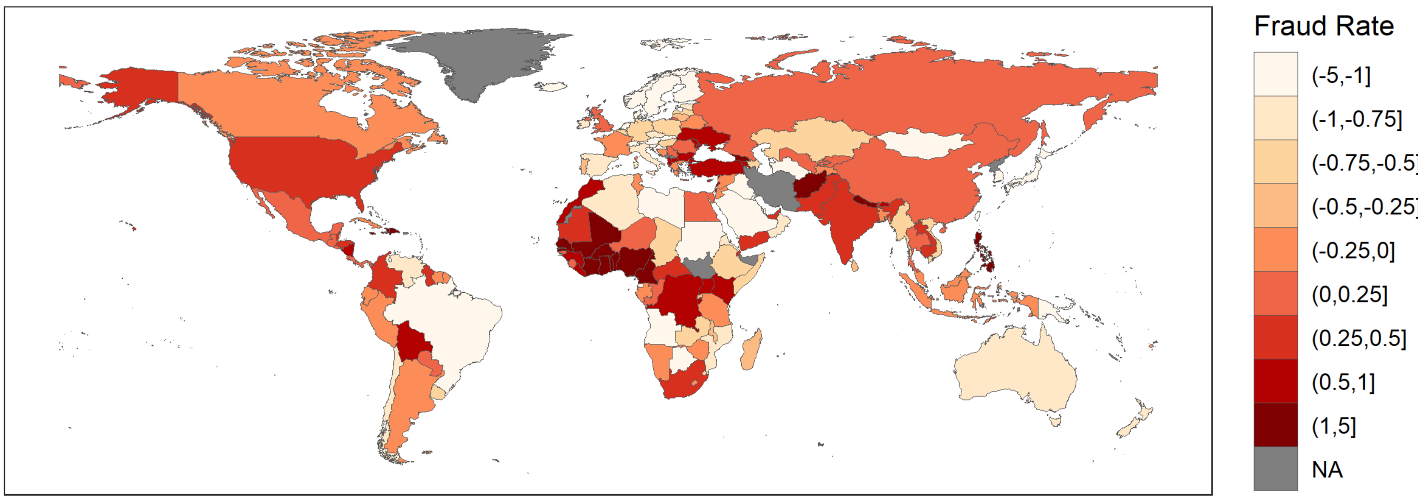
Notes. Maps show estimated fraud rates by country. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the overall distribution.

Figure A6: Estimated Fraud Rates, FTC and econsumer.gov



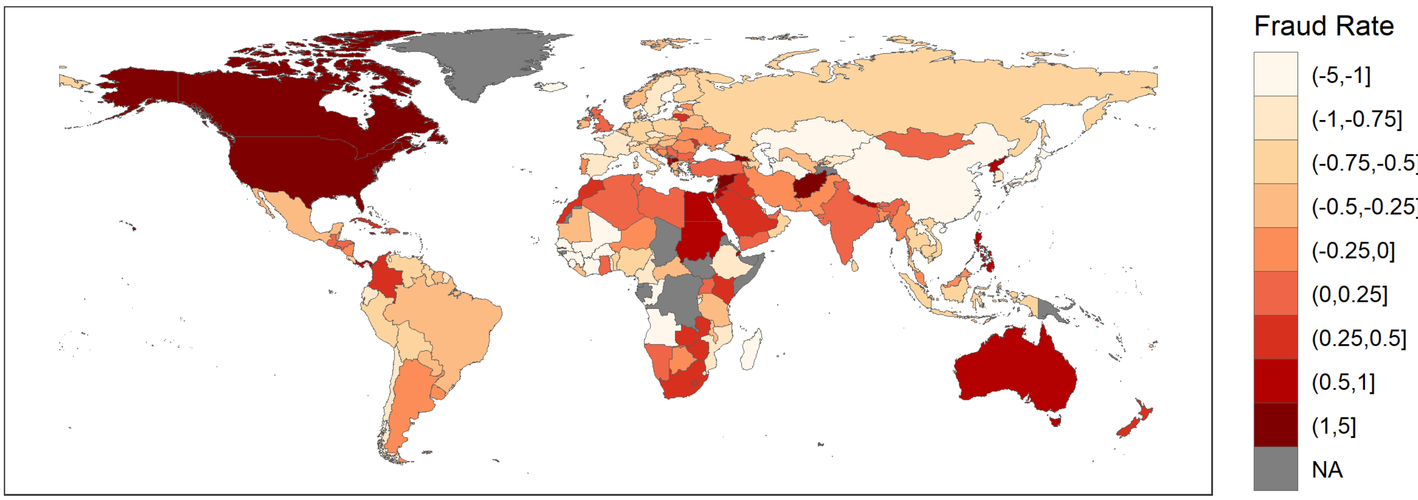
Notes. Maps show estimated fraud rates by country, only using complaints from FTC and econsumer.gov sources in Consumer Sentinel. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution across all Consumer Sentinel sources.

Figure A7: Estimated Fraud Rates, Consumer Sentinel Money Transfer Companies



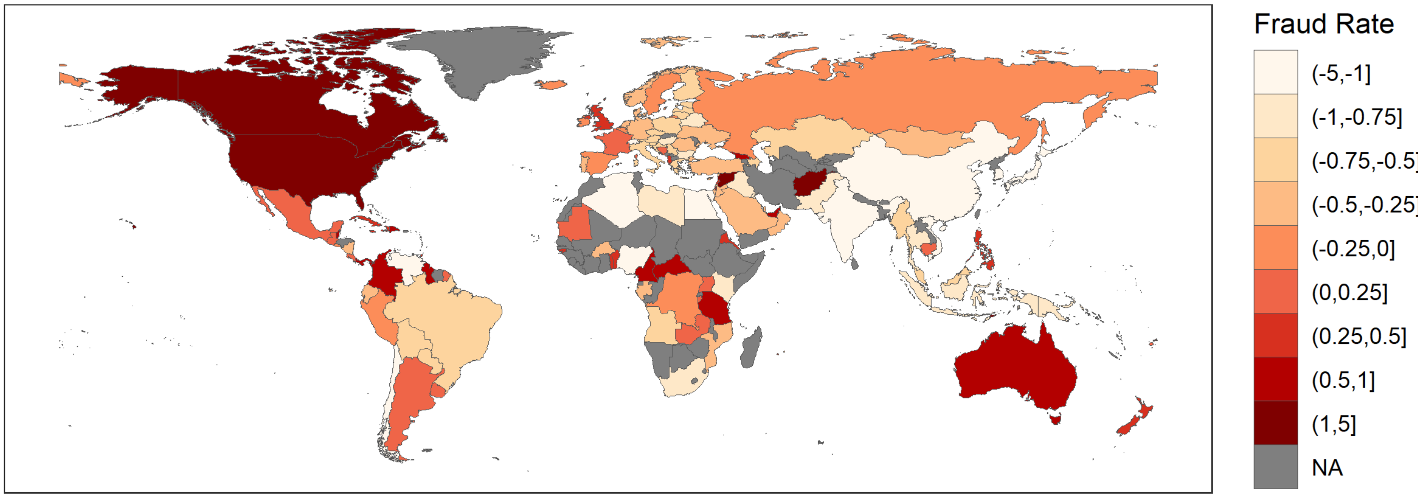
Notes. Maps show estimated fraud rates by country, only using complaints from Consumer Sentinel for MoneyGram and Western Union only. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution across all Consumer Sentinel sources.

Figure A8: Estimated Fraud Rates, Consumer Sentinel Data, Complaints About Online Shopping



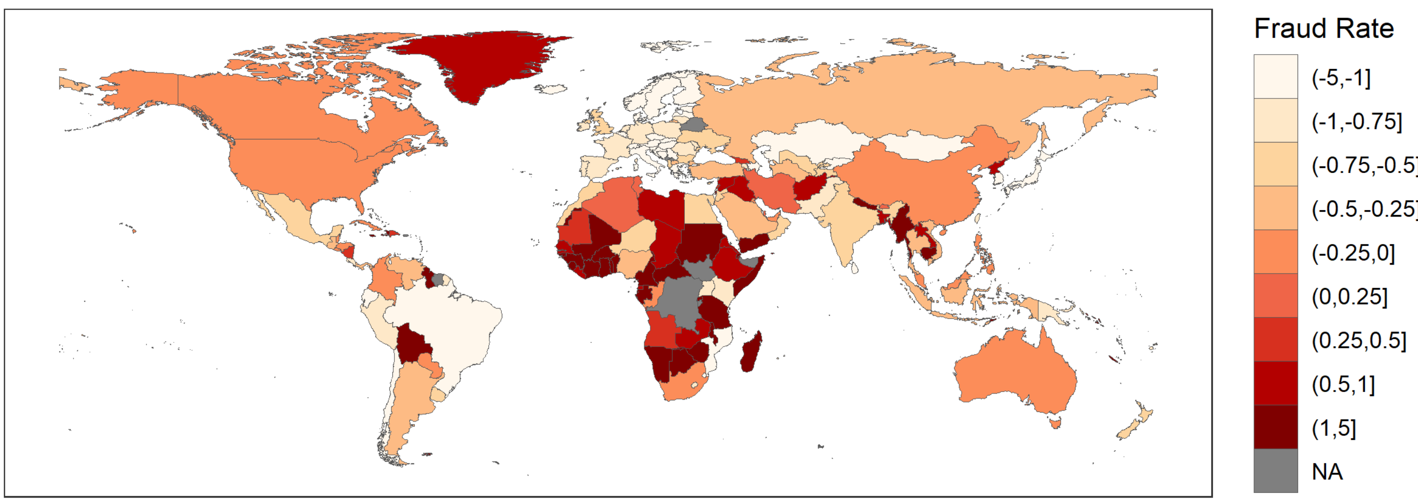
Notes. Maps show estimated fraud rates by country, only using complaints from Consumer Sentinel. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution across all Consumer Sentinel sources.

Figure A9: Estimated Fraud Rates, MT Data, Complaints About Online Shopping



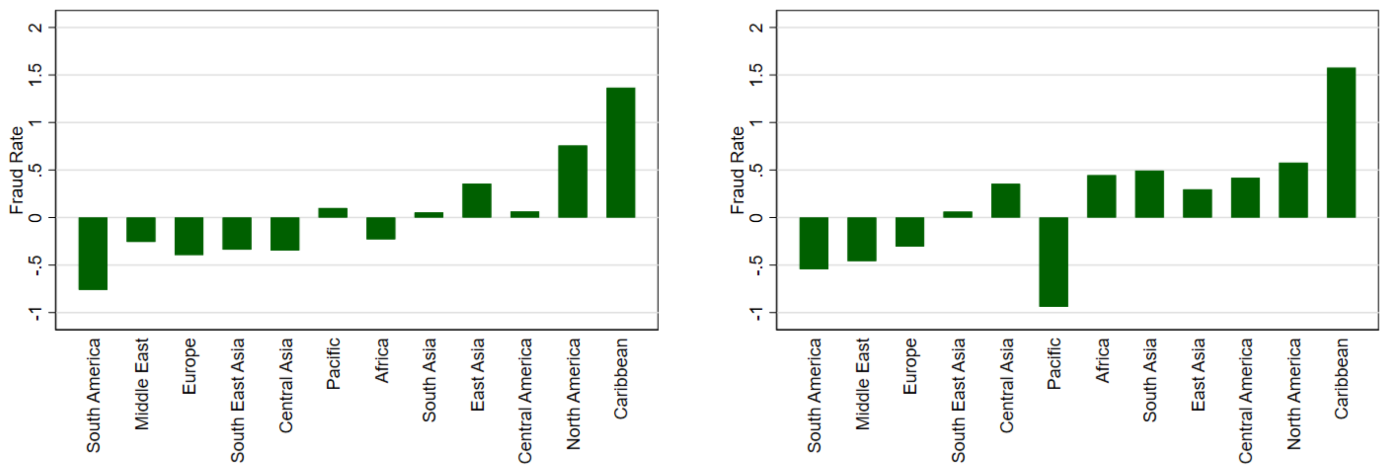
Notes. Maps show estimated fraud rates by country, only using complaints from MT. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution across all Consumer Sentinel sources.

Figure A10: Estimated Fraud Rates, Consumer Sentinel Data, Relative to Trade in Services



Notes. Maps show estimated fraud rates by country, using. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The trade data are limited to only trade in services. The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Category breaks roughly correspond to quantiles of the distribution across all sources.

Figure A11: Estimated Fraud Rates by Region, Consumer Sentinel Contributors



a) FTC

b) Money Transfer

Notes. Figure shows population-weighted mean fraud rates by region, using complaints in Consumer Sentinel from the FTC and econsumer.gov only (panel a) and Western Union and MoneyGram (panel b). Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation (11). The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one. Regions groupings come from the ITC Dynamic Gravity Dataset, with Eurasia combined with Central Asia. Bars are sorted according to rankings in the overall Consumer Sentinel data.

Table A1: Complaint Categories, Consumer Sentinel

	(1) Cross-Border	(2) US Domestic
Imposter Scams	0.255	0.171
Online Shopping and Negative Reviews	0.160	0.051
Prizes, Sweepstakes and Lotteries	0.060	0.058
Shop-at-Home and Catalog Sales	0.048	0.018
Internet Services	0.040	0.032
Fake/Counterfeit Check Scams	0.039	0.012
Investment Related	0.032	0.009
Business and Job Opportunities	0.027	0.013
Travel, Vacations and Timeshare Plans	0.024	0.017
Advance Payments for Credit Services	0.021	0.007
Health Care	0.008	0.024
Telephone and Mobile Services	0.007	0.039
Auto Related	0.005	0.054
Banks and Lenders	0.005	0.071
Debt Collection	0.003	0.056
Credit Cards	0.003	0.025
Credit Bureaus, Information Furnishers and Report Users	0.001	0.070
Other	0.039	0.073
Unspecified/Uncategorized	0.223	0.201

Notes. The table shows the share of complaints by category. The US-based column shows the number of complaints that include the US as consumer and company. The cross-border column is the number of complaints that include different consumer and company countries. The “Other” category includes 14 different categories of complaints. “Fake Check Scams” and “Counterfeit Check Scams” have been combined into one category.

Table A2: Complaint Categories, MT Data

	(1) Cross-Border	(2) US Domestic
On-Line Purchases	0.257	0.361
Lottery/Prize	0.147	0.093
Advance Fee/Prepayment	0.116	0.071
On-Line Relationship	0.097	0.028
Emergency Funds	0.090	0.042
Job	0.042	0.076
Loan	0.038	0.014
Counterfeit Check/Money Order	0.034	0.049
Rental Property	0.020	0.034
Item For Sale By Victim	0.017	0.070
Anti-Virus Scam	0.014	0.006
Border Crossing/Smuggling	0.014	0.007
Investment	0.011	0.007
Other	0.054	0.084
Unspecified/Uncategorized	0.049	0.057

Notes. The table shows the share of complaints by category. The US-based column shows the number of complaints that include the US as consumer and company. The cross-border column is the number of complaints that include different consumer and company countries. The "Other" category includes 28 different categories of complaints.

Table A3: Heterogeneity in Gravity Results by Consumer Sentinel Data Source

	(1) FTC	(2) Money Transfer	(3) Cyber Crime
ln(International Distance)	-0.321***	-0.775***	-0.0733
	(0.0539)	(0.0694)	(0.150)
ln(Intranational Distance)	-0.170*	0.185	-0.897***
	(0.0821)	(0.238)	(0.194)
Common Language	0.521***	1.229***	0.405*
	(0.0993)	(0.114)	(0.182)
Contiguity	0.130	-0.398*	0.516*
	(0.144)	(0.157)	(0.202)
Colony	0.178	-0.0576	0.193
	(0.158)	(0.140)	(0.178)
Same-Country Pair	1.294	-6.233***	7.663***
	(0.770)	(1.790)	(1.178)
N	63448	63448	63448
Company Country FE	X	X	X
Consumer Country FE	X	X	X
Trade Agreement Controls	X	X	X

Notes. Table shows estimates of equation 11, separately by the source of data. The dependent variable is the number of complaints from consumers in country i about companies in country j, using the specified data source. Column 1 includes data from Consumer Sentinel for the FTC and econsumer.gov, an international effort by members of the International Consumer Protection and Enforcement Network (ICPEN) to combat fraud, led by the FTC. Column 2 includes Consumer Sentinel data from MoneyGram and Western Union for 2014-2021. Columns 3 and 4 include data from a large money transfer company for 2004 to 2014. Column 4 includes sum of the dollar value of the wired funds related to the complaint, rather than the count of complaints. International and intranational distance are calculated as population-weighted distances in kilometers across main cities. Trade controls include separate dummies for whether the two countries had engaged in preferential trade agreements, at least one customs union, economic integration agreements, free trade agreements, and partial scope agreements at any point between 2014-2021. Model is estimated using Poisson Pseudo Maximum Likelihood. 56 of the possible 63,504 pairs are excluded due to missing control variables. Robust standard errors.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table A4: Heterogeneity in Gravity Results by Consumer Sentinel Complaint Category

	(1)	(2)	(3)	(4)	(5)
	Imposter	Online Shopping	Lotteries	Services	Check Scams
ln(International Distance)	-0.337***	-0.328***	-1.237***	-0.430***	-0.785***
	(0.0860)	(0.0747)	(0.127)	(0.116)	(0.0700)
ln(Intranational Distance)	-0.597***	-0.140	-0.0856	-0.411***	0.763*
	(0.100)	(0.120)	(0.226)	(0.100)	(0.355)
Common Language	0.740***	0.508***	0.641***	0.373*	1.022***
	(0.106)	(0.146)	(0.151)	(0.150)	(0.156)
Contiguity	0.183	0.226	-0.177	-0.584*	-0.00962
	(0.162)	(0.171)	(0.283)	(0.293)	(0.184)
Colony	0.0811	0.193	0.646**	0.742***	0.414***
	(0.123)	(0.165)	(0.234)	(0.181)	(0.125)
Same-Country Pair	3.802***	0.543	-7.589***	1.440	-9.709***
	(0.731)	(1.078)	(1.981)	(1.127)	(2.783)
N	63448	63448	63448	63448	63448
Company Country FE	X	X	X	X	X
Consumer Country FE	X	X	X	X	X
Trade Agreement Controls	X	X	X	X	X

Notes. Table shows estimates of equation 11, for the largest five categories of complaints in the Consumer Sentinel data. The dependent variable is the number of complaints in the specified category from consumers in country i about companies in country j. Column 1 includes complaints labelled as imposter scams. Column 2 includes complaints related to online shopping, catalog sales, and negative reviews, as well as shop-at-home products. Column 3 includes complaints related to prizes, sweepstakes, and lotteries. Column 4 includes complaints about internet services. Column 5 includes complaints about fake or counterfeit check scams. International and intranational distance are calculated as population-weighted distances in kilometers across main cities. Trade controls include separate dummies for whether the two countries had engaged in preferential trade agreements, at least one customs union, economic integration agreements, free trade agreements, and partial scope agreements at any point between 2014-2021. Model is estimated using Poisson Pseudo Maximum Likelihood. 56 of the possible 63,504 pairs are excluded due to missing control variables. Robust standard errors. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A5: Heterogeneity in Gravity Results by MT Complaint Category

	(1) Online	(2) Lottery	(3) Prepayment	(4) Relationship	(5) Emergency
ln(International Distance)	-0.577***	-0.963***	-0.322	-0.152	-0.546***
	(0.114)	(0.266)	(0.194)	(0.206)	(0.125)
ln(Intranational Distance)	-0.101	-1.443***	-0.664	-0.329	0.0586
	(0.203)	(0.331)	(0.400)	(0.321)	(0.219)
Common Language	0.878***	0.847*	2.014***	1.883***	1.162***
	(0.196)	(0.389)	(0.240)	(0.287)	(0.227)
Contiguity	-0.295	-0.948*	-0.918*	-0.707	0.211
	(0.198)	(0.426)	(0.466)	(0.407)	(0.278)
Colony	0.245	-0.648	0.231	-0.0555	0.335
	(0.169)	(0.436)	(0.293)	(0.184)	(0.220)
Same-Country Pair	-2.957	2.879	4.133	2.248	-2.230
	(1.639)	(3.819)	(2.874)	(2.517)	(1.772)
N	63448	63448	63448	63448	63448
Company Country FE	X	X	X	X	X
Consumer Country FE	X	X	X	X	X
Trade Agreement Controls	X	X	X	X	X

Notes. Table shows estimates of equation 11, for the largest five categories of complaints in the data from MT, a large money transfer company. The dependent variable is the number of complaints in the specified category from consumers in country i about companies in country j. Column 1 includes complaints labelled as on-line purchases. Column 2 includes complaints related to lotteries and prizes. Column 3 includes complaints related to advanced fee or prepayment scams. Column 4 includes complaints about online relationships. Column 5 includes complaints about emergency scams, including disaster relief scams. International and intranational distance are calculated as population-weighted distances in kilometers across main cities. Trade controls include separate dummies for whether the two countries had engaged in preferential trade agreements, at least one customs union, economic integration agreements, free trade agreements, and partial scope agreements at any point between 2014-2021. Model is estimated using Poisson Pseudo Maximum Likelihood. 56 of the possible 63,504 pairs are excluded due to missing control variables. Robust standard errors. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A6: Gravity Estimates, Trade, For Country Pairs with Complaints Data

	(1)	(2)	(3)	(4)
ln(International Distance)	-0.761***	-0.798***	-0.795***	-0.751***
	(0.0532)	(0.0514)	(0.0776)	(0.0337)
ln(Intranational Distance)	-0.369***	-0.428***	-0.429***	
	(0.0761)	(0.0744)	(0.0794)	
Common Language	0.365***	0.272**	0.271**	0.236***
	(0.0825)	(0.0878)	(0.0871)	(0.0588)
Contiguity	0.215	0.416***	0.419***	0.135*
	(0.111)	(0.0928)	(0.102)	(0.0611)
Colony	0.250	0.194	0.195	0.0907
	(0.137)	(0.131)	(0.126)	(0.0693)
Same-Country Pair			0.0323	
			(0.699)	
N	63448	63448	63448	63196
Company Country FE	X	X	X	X
Consumer Country FE	X	X	X	X
Trade Agreement Controls		X	X	
Same-country pairs omitted				X

Notes. Table shows estimates of equation 11. The dependent variable is the trade volume across all industries from the ITC International Trade and Production Database, in real dollars. Trade volume is set to zero for country pairs without any complaints in the Consumer Sentinel data across all sources. International and intranational distance are calculated as population-weighted distances in kilometers across main cities. Trade controls include separate dummies for whether the two countries had engaged in preferential trade agreements, at least one customs union, economic integration agreements, free trade agreements, and partial scope agreements at any point between 2014-2021. Model is estimated using Poisson Pseudo Maximum Likelihood. 56 of the possible 63,504 pairs are excluded due to missing control variables. Robust standard errors. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A7: Gravity Estimates, Trade in Services

	(1)	(2)	(3)	(4)
ln(International Distance)	-0.706***	-0.708***	-0.492***	-0.790***
	(0.0487)	(0.0488)	(0.0798)	(0.0489)
ln(Intranational Distance)	-0.0239	-0.0745	-0.0932	
	(0.0748)	(0.0771)	(0.0794)	
Common Language	0.516***	0.448***	0.419***	0.286**
	(0.107)	(0.105)	(0.105)	(0.0907)
Contiguity	-0.0201	0.326*	0.539**	0.0660
	(0.152)	(0.156)	(0.171)	(0.0848)
Colony	0.729***	0.590**	0.655***	0.0131
	(0.188)	(0.186)	(0.184)	(0.117)
Same-Country Pair			2.083**	
			(0.646)	
N	63448	63448	63448	63196
Company Country FE	X	X	X	X
Consumer Country FE	X	X	X	X
Trade Agreement Controls		X	X	
Same-country pairs omitted				X

Notes. Table shows estimates of equation 11. The dependent variable is the trade volume across service industries from the ITC International Trade and Production Database, in real dollars. International and intranational distance are calculated as population-weighted distances in kilometers across main cities. Trade controls include separate dummies for whether the two countries had engaged in preferential trade agreements, at least one customs union, economic integration agreements, free trade agreements, and partial scope agreements at any point between 2014-2021. Model is estimated using Poisson Pseudo Maximum Likelihood. 56 of the possible 63,504 pairs are excluded due to missing control variables. Robust standard errors. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A8: Countries with the Highest Estimated Fraud Rate, Consumer Sentinel Data

Country	Fraud Rate
JAMAICA	3.430
BENIN	2.754
GAMBIA	2.358
SYRIAN ARAB REPUBLIC	2.334
GEORGIA	2.190
DOMINICAN REPUBLIC	2.074
GHANA	1.953
TOGO	1.944
BURKINA FASO	1.888
DJIBOUTI	1.864
COMOROS	1.814
CAMEROON	1.806
HAITI	1.754
UNITED STATES	1.555
COTE D'IVOIRE	1.529
CANADA	1.452
HONG KONG	1.384
NICARAGUA	1.309
MACEDONIA, THE FORMER YUG...	1.301
MALI	1.243
SENEGAL	1.233
BHUTAN	1.180
PANAMA	1.175
CENTRAL AFRICAN REPUBLIC	1.104
NIGERIA	1.089

Notes. Table shows list of 25 countries with highest estimated fraud rates, limited to countries with a population of at least 500,000. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation 11. The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one.

Table A9: Countries with the Highest Estimated Fraud Rate, Consumer Sentinel Data, No Population Limitation

Country	Fraud Rate
ANGUILLA	3.129
JAMAICA	2.957
MONTSERRAT	2.548
BENIN	2.349
DOMINICA	2.087
GAMBIA	1.993
SYRIAN ARAB REPUBLIC	1.972
TURKS AND CAICOS ISLANDS	1.860
GEORGIA	1.842
SAO TOME AND PRINCIPE	1.780
DOMINICAN REPUBLIC	1.738
GHANA	1.629
TOGO	1.621
GRENADA	1.572
BURKINA FASO	1.570
DJIBOUTI	1.549
ST. KITTS AND NEVIS	1.505
COMOROS	1.504
CAMEROON	1.497
BELIZE	1.459
HAITI	1.450
ANTIGUA AND BARBUDA	1.422
ST. VINCENT AND THE GRENA...	1.409
UNITED STATES	1.271
BARBADOS	1.250

Notes. Table shows list of 25 countries with highest estimated fraud rates. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation 11. The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one.

Table A10: Countries with the Highest Estimated Fraud Rate, MT Data

Country	Fraud Rate
JAMAICA	3.037
BENIN	2.655
CAMEROON	2.338
HAITI	2.128
GHANA	1.997
DOMINICAN REPUBLIC	1.795
NEPAL	1.735
TOGO	1.630
SENEGAL	1.552
COTE D'IVOIRE	1.505
BURKINA FASO	1.504
NIGERIA	1.473
LEBANON	1.458
GEORGIA	1.392
MOLDOVA, REPUBLIC OF	1.390
GAMBIA	1.319
PHILIPPINES	1.302
ROMANIA	1.199
UKRAINE	1.168
CAPE VERDE	1.135
UNITED KINGDOM	1.130
CANADA	1.097
CONGO, DEMOCRATIC REPUBLI...	1.064
INDIA	1.061
CHINA	0.962

Notes. Table shows list of 25 countries with highest estimated fraud rates, limited to countries with a population of at least 500,000, using complaints data from a large money transfer company. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation 11. The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one.

Table A11: Countries with the Highest Estimated Fraud Rate, ACCC

Country	Fraud Rate
AUSTRALIA	11.267
CENTRAL AFRICAN REPUBLIC	1.187
FIJI	0.912
SYRIAN ARAB REPUBLIC	0.889
UNITED KINGDOM	0.869
MAURITANIA	0.816
GUINEA-BISSAU	0.758
DJIBOUTI	0.727
COMOROS	0.726
BURUNDI	0.686
LIBERIA	0.669
GAMBIA	0.661
CONGO, DEMOCRATIC REPUBLI...	0.631
TUNISIA	0.599
BENIN	0.582
HONG KONG	0.549
SENEGAL	0.534
GUINEA	0.519
UNITED STATES	0.499
JAMAICA	0.497
TOGO	0.482
LESOTHO	0.469
GABON	0.467
CHAD	0.443
EQUATORIAL GUINEA	0.379

Notes. Table shows list of 25 countries with highest estimated fraud rates, limited to countries with a population of at least 500,000, using complaints data from the ACCC. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation 11. The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one.

Table A12: Countries with the Highest Estimated Fraud Rate, Consumer Sentinel Data, Money Transfer Companies

Country	Fraud Rate
JAMAICA	2.582
BENIN	2.569
GAMBIA	2.187
TOGO	2.074
GEORGIA	2.056
BURKINA FASO	2.002
GHANA	1.907
CAMEROON	1.843
HAITI	1.774
COTE D'IVOIRE	1.726
DOMINICAN REPUBLIC	1.607
MALI	1.554
SENEGAL	1.505
COMOROS	1.361
PHILIPPINES	1.344
NIGERIA	1.289
NEPAL	1.226
NICARAGUA	1.144
BHUTAN	1.113
UKRAINE	1.099
LIBERIA	1.030
ALBANIA	0.969
PALESTINE, STATE OF	0.950
CAPE VERDE	0.937
CONGO, DEMOCRATIC REPUBLI...	0.889

Notes. Table shows list of 25 countries with highest estimated fraud rates, limited to countries with a population of at least 500,000, using Consumer Sentinel complaints data from MoneyGram and Western Union. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation 11. The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one.

Table A13: Countries with the Highest Estimated Fraud Rate, Consumer Sentinel Data, Complaints About Online Shopping

Country	Fraud Rate
AFGHANISTAN	3.253
SYRIAN ARAB REPUBLIC	2.548
MACEDONIA, THE FORMER YUG...	2.501
GAMBIA	2.424
UNITED STATES	2.091
BURKINA FASO	2.016
COTE D'IVOIRE	2.014
JAMAICA	1.970
COMOROS	1.872
CANADA	1.709
BENIN	1.691
HONG KONG	1.670
DOMINICAN REPUBLIC	1.623
MALI	1.568
PANAMA	1.495
GEORGIA	1.417
CENTRAL AFRICAN REPUBLIC	1.380
GHANA	1.341
SOMALIA	1.340
TOGO	1.325
KOREA, DEMOCRATIC PEOPLE'...	1.249
CYPRUS	1.247
PHILIPPINES	1.109
NEPAL	0.968
MACAU	0.938

Notes. Table shows list of 25 countries with highest estimated fraud rates, limited to countries with a population of at least 500,000, using Consumer Sentinel complaints data from MoneyGram and Western Union. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation 11. The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one.

Table A14: Countries with the Highest Estimated Fraud Rate, MT Data, Complaints About Online Shopping

Country	Fraud Rate
CAMEROON	3.162
BENIN	2.597
DOMINICAN REPUBLIC	2.079
JAMAICA	1.950
ROMANIA	1.881
TOGO	1.765
AFGHANISTAN	1.704
UNITED KINGDOM	1.622
GEORGIA	1.606
DJIBOUTI	1.518
COMOROS	1.501
CROATIA (local name: Hrva...	1.498
BURKINA FASO	1.468
GHANA	1.416
NIGERIA	1.321
CHINA	1.203
LEBANON	1.176
SENEGAL	1.171
MOLDOVA, REPUBLIC OF	1.162
SYRIAN ARAB REPUBLIC	1.092
COTE D'IVOIRE	1.010
ITALY	0.906
GAMBIA	0.904
HAITI	0.877
MALI	0.843

Notes. Table shows list of 25 countries with highest estimated fraud rates, limited to countries with a population of at least 500,000, using Consumer Sentinel complaints data from MoneyGram and Western Union. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation 11. The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one.

Table A15: Countries with the Highest Estimated Fraud Rate, Consumer Sentinel Data, Relative to Trade in Services

Country	Complaint Score
BENIN	2.466
GHANA	2.384
CAMEROON	2.363
MALI	2.166
BURKINA FASO	2.160
TOGO	2.101
HAITI	1.955
NEPAL	1.916
YEMEN	1.840
BOLIVIA	1.798
GAMBIA	1.777
COTE D'IVOIRE	1.685
SIERRA LEONE	1.680
CENTRAL AFRICAN REPUBLIC	1.579
GABON	1.530
MYANMAR	1.512
CAMBODIA	1.439
ZIMBABWE	1.386
SUDAN	1.360
GUINEA	1.358
PALESTINE, STATE OF	1.308
MADAGASCAR	1.308
GUINEA-BISSAU	1.287
NAMIBIA	1.270
TANZANIA, UNITED REPUBLIC...	1.266

Notes. Table shows list of 25 countries with highest estimated fraud rates, limited to countries with a population of at least 500,000. Estimated fraud rates are the difference between the company fixed effects resulting from estimation of the two models in equation 11. The trade regression is limited to trade volume in service industries. The model is estimated using Poisson Pseudo Maximum Likelihood and controls for (log) intranational and international distance, contiguity, colonial relationships, shared language, and trade agreements. The resulting difference in fixed effects is standardized to have mean zero and standard deviation of one.

Table A16: Fraud Scores and Individual Country Characteristics

	(1) CS	(2) MT	(3) ACCC
Regulatory Quality	-0.111	-0.240**	-0.0847
	(0.0731)	(0.0826)	(0.0765)
r2	0.0117	0.0529	0.00651
N	176	167	174
Rule of Law	-0.170*	-0.293***	-0.0779
	(0.0674)	(0.0783)	(0.0735)
r2	0.0283	0.0814	0.00563
N	176	167	174
Government Effectiveness	-0.186**	-0.306***	-0.135
	(0.0699)	(0.0751)	(0.0732)
r2	0.0339	0.0892	0.0171
N	176	167	174

Notes. Table shows estimates regressions of country-level estimated complaint rates on country characteristics. GDP and population come from the US ITC gravity dataset. Other country characteristics come from the WGI. Robust standard errors. $*p < 0.05, **p < 0.01, ***p < 0.001$