The geography of payment activity on PayPal*

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Abstract: We use data from the electronic payments company PayPal to study the geography of online payment activity. An empirical gravity model confirms previous findings pertaining to e-commerce, namely a distance elasticity of payment value that is substantially lower than is typically observed in conventional international trade data. Our rich dataset allows us to study margins of payment activity, and we find that the firm extensive margin is considerably less sensitive to geographic frictions than is payment value. We investigate the reduced role of this extensive margin of trade using an analytical framework that predicts that the size of a firm’s exports is positively related to the average distance over which those exports are sold. We find a considerably weaker link between the scale and the geographic scope of PayPal merchants’ exports on the platform than has been observed among firms engaged in conventional international trade. In the theoretic framework, a cross-sectional relationship between export scale and geographic scope emerges over time because firms’ total export growth is partially attributed to their entry into ever more distant markets. In merchant-level regressions, we find that the age of PayPal merchants’ accounts has only marginal effects on the scale and average distance of their export sales on the platform. Overall, our findings suggest that PayPal – and perhaps e-commerce more broadly – offers disproportionate benefits to relatively small and/or new trading firms, because it facilitates their access to geographically distant markets.

JEL codes: L86, G23, F14, F39

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Section I. Introduction

E-commerce represents a fast-growing share of all retail sales activity. U.S. Census Bureau (2020a) reports that e-commerce grew from just over 4 percent of U.S. retail transactions in 2010 to more than 12 percent in the fourth quarter of 2019.¹ E-commerce is also important globally, and cross-border sales via e-commerce are growing rapidly. UNCTAD (2020) estimates that approximately 1.45 billion people shopped online in 2018. The same estimates indicate that the share of online shoppers who made international purchases rose from 15 percent in 2015 to 23 percent in 2018, and that cross-border business-to-consumer sales in 2018 totaled $404 billion.² The electronic payments firm PayPal processes payments for a sizable share of this market, and has a global footprint.

In this paper we use proprietary data from PayPal to study the geography of international e-commerce activity by PayPal sellers (called here “merchants”). Our purpose is to compare and contrast our findings with the now vast literature on the geography of international trade, and, more specifically, a small but growing literature on the geography of e-commerce. We also use our rich data to generate stylized facts that are new to the e-commerce literature, and compare these facts with counterparts from the broader literature on international trade. Of particular interest are the link between the merchant extensive margin of trade and the distance elasticity of payment value, and related links between the scale of merchants’ exports on the platform and the geographic scope of those sales. We apply a theoretical and empirical framework proposed by Chaney (2018) to study international sales of PayPal merchants located in eight countries that differ in size, geographic location, and level of development. Finally, we estimate merchant-level regressions that relate the age of merchants’ PayPal accounts to the scale and geographic scope of their export sales on the platform.

The data provided by PayPal include the universe of transactions that took place on the platform during a 24-day sample from 2016.³ Our first exercises generate summary statistics that characterize payment activity on the platform. As might be expected, international PayPal transactions are typically much smaller than those observed in conventional international trade. The average value of a transaction for the median merchant in our sample is just $295.⁴ In contrast to what is observed in conventional international trade data, merchants in our sample typically serve a large number of destinations and do so

¹ These figures pre-date the boom in online retail activity resulting from the Covid-19 pandemic. Preliminary estimates put the e-commerce share at more than 15 percent of retail sales in the second quarter of 2020. See U.S. Census Bureau (2020b).
² Figures from 2015 are reported in UNCTAD (2019).
³ Further details about the data are provided in Section II, below. The statistics that follow represent results from a sample that excludes merchants with less than $10,000 of export sales within our sample. We explain the reasons for this trimming later in the paper.
⁴ The de minimis value required for U.S. import shipments to be assessed tariffs was raised from $200 to $800 in 2016. A large majority of the transactions we study lie below the current de minimis threshold.
over very long distances. Half of the merchants in the sample receive payments from 17 or more markets in the 24-day period, and the average distance of export sales for the median firm is 8,133 kilometers.

In a standard empirical gravity model, we estimate a distance elasticity of payment value of -0.58 on the PayPal platform, a value that is considerably smaller than the unitary distance elasticity commonly observed in the international trade literature.\(^5\) The estimate is consistent with two prior estimates of the distance elasticity found in studies of international transactions on online marketplaces (e.g. eBay).\(^6\) As a payment mechanism, PayPal serves a different function than the online marketplaces. It is also likely that the PayPal data represent a much broader swathe of online transactions, including, for example, payments for many services. The consistency of the distance elasticity results across the two types of internet transaction data suggests that the low distance elasticity is a general feature of trade over the internet, rather than an outcome that is attributable specifically to online marketplaces.

Our data also contain information on the number of bilateral transactions and number of merchants receiving payments along each bilateral route. These data allow us to estimate extensive margins of international payment activity. Nearly all of the geographic variation in payment value can be explained by variation in transaction numbers; average transaction value grows only modestly with distance. By contrast, the distance elasticity of the number of merchants receiving payments along a bilateral route is only -0.31. The modest role for the firm extensive margin is notably at odds with evidence from the conventional international trade literature.\(^7\) The contribution of the firm extensive margin to the overall distance elasticity of payment value is also much lower than is observed in the only estimate of the kind from the online marketplace data.\(^8\)

In the literature on conventional international trade flows, a key operating mechanism connecting the firm extensive margin of trade to geographic frictions is a strong relationship between the *scale* of a firm’s exports and the *geographic scope* of its export activity: Firms with larger total exports also export to more and to more distant international markets.\(^9\) Chaney (2018) offers a novel theory that explains

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\(^5\) Disdier and Head (2008) conduct a meta-analysis of empirical studies of the distance elasticity of trade flows in the gravity model of trade, and report a strong central tendency around the value of -1. Head and Mayer (2013) show kernel density estimates from an even larger sample of distance elasticity estimates, and these are still centered around the value of -1.

\(^6\) Lendle, *et al.* (2016) estimate distance elasticities between -0.35 and -0.51 in a sample of international transactions on eBay. In samples that include international transactions on Mercado Libre, Hortacsu, *et al.* (2009) estimate distance elasticities of -0.55 and -0.38. Lendle, *et al.* (2013) estimate a much larger distance elasticity (-1.5) in a sample of international eBay transactions. Fan, *et al.* (2018) and Hortacsu, *et al.* (2009) estimate lower elasticities in domestic transactions on Alibaba (China) and eBay (U.S.), respectively.

\(^7\) In a study of U.S. exporters, Bernard, *et al.* (2007) find a distance elasticity of the number of exporting firms of -1.14, which represents 84 percent of the total distance elasticity of export value, -1.36.

\(^8\) Of the studies of trade involving online marketplaces, only Lendle *et al.* (2013) estimates a distance elasticity for the number of exporting firms. In a sample of international sales on eBay, they estimate this value to be -1.55.

these relationships as the outcome of a process in which the growth of a firm’s total exports is tied to the growth in the average distance of its export sales. We estimate the parameters of the Chaney theory for eight countries that vary in size, geographic location, and level of development. The link between the scale of export activity and its geographic scope is considerably weaker in our data than in the conventional firm-level trade data used in Chaney (2018). Relatively small PayPal merchants sell over distances that are nearly as large as those of the largest firms in the dataset. This is consistent with an interpretation that the internet reduces the incidence of geography in a way that favors relatively small firms.

One of the assumptions that underlie Chaney’s theory is that the distribution of firms’ export sales follows Zipf’s Law, which states that the value of a firm’s sales is inversely proportional to its rank in the distribution of firm sales. We find that Zipf’s Law holds for PayPal merchants in China, in the United States, and (approximately) for the world as a whole, but fails among countries with smaller numbers of exporting merchants.

Conventional explanations for Zipf’s Law in this context would posit that the growth rate of PayPal merchants’ international sales is independent of their existing sizes. The Chaney theory incorporates this explanation for Zipf’s Law, and posits a related process of growth in the average distance of export sales. Our cross-sectional data lack a temporal dimension, so we are unable to study growth rates. However, we do have information on the age of merchants’ PayPal accounts. In merchant-level regressions we estimate the conditional effect of account age on export sales and average export distance. We find that account age plays only a marginal role in explaining either outcome. New PayPal merchants are able to sell over vast distances and do so at scale.

This paper lies at the intersection of three strands of literature. First, a small, but growing number of papers study the geography of online commerce. Most of these papers study transactions made in online marketplaces, including e-Bay, AliBaba, and Mercado Libre.10 Like ours, most of these papers estimate distance elasticities of trade that are lower than is observed in most studies of conventional international trade. Our data represent online payment activity, rather than sales on an online marketplace.11 Our data are also more representative of online commerce than are data from the online marketplaces. The results suggest that the mechanisms thought to explain the low distance elasticity in online marketplaces may generalize to e-commerce more broadly. We contribute to the literature on the

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11 The online marketplaces can be best understood as online auction houses or virtual department stores whose primary role is to facilitate the matching of buyers and sellers. PayPal, on the other hand, is a global financial intermediary that provides users with payment capabilities in national and international transactions.
geography of e-commerce by demonstrating that the firm extensive margin plays only a minor role in explaining trade over distance, and by linking the near-absence of this extensive margin to the absence of a strong relationship between export scale and the geographic scope of exports on the platform.

Second, our paper relates to a large literature on the role of firms in international trade. We use this literature to map the ways in which trade accomplished by payments on the PayPal platform differs from conventional international trade flows. The transactions we study are much smaller than in conventional trade, and geographic frictions play a much smaller role in determining bilateral trade flows. Notably, we document a much smaller distance elasticity of the firm extensive margin of trade. We are among the first to apply the recently developed theory of Chaney (2018), which we use to study the relationship between the scale and geographic scope of PayPal merchants’ sales. In our data, the scale of merchants’ activity is nearly independent of the geographic scope of that activity, a finding that contrasts sharply with commonly observed outcomes in conventional international trade data. The absence of a strong link between scale and scope would appear to be a key reason for the small contribution of the firm extensive margin to the distance elasticity of trade, and thus for the low overall distance elasticity of international online payment value. The weak link between scale and geographic scope also suggests that firms that are relatively small in e-commerce do not bear the same relative disadvantage in distant markets as do small firms engaged in conventional international trade.

Finally, our paper also offers an empirical contribution to the literature on power laws in economics. Gabaix (2009) reviews this literature, which shows that the empirical distribution of many economic entities (firms, cities, etc.) can be summarized efficiently with a mathematical power law known as Zipf’s Law. The primary theoretical explanation for Zipf’s law in this literature is that it emerges from a stochastic growth process in which the average growth rate is independent of firm size, and is stable over time. The short history and rapid growth of PayPal activity might lead one to believe that these conditions are unlikely to hold in the PayPal data. Nevertheless, we observe Zipf’s law among data on merchants in China, in the United States and, approximately, in the world as a whole. We are unable to test for the underlying mechanisms, but cross-sectional regressions of merchants’ total international sales on account age show no evidence of a consistent relationship between the age of a merchant’s account and its sales on the platform. It appears that new PayPal merchants are able to serve distant as well as local markets, and to do so at scale.

12 Conventional theories that predict a gravity-like relationship in international trade (e.g., Anderson and van Wincoop (2003), Eaton and Kortum (2003), Melitz (2003)) are poorly suited for analysis of these data. These are typically general equilibrium models in which the bilateral trade pattern is determined by iceberg trade costs and responses to those costs. At least some part of the transactions studied here would be digital goods for which an iceberg cost representation seems especially inappropriate.
The remainder of the paper is organized as follows. In Section II we review the operation of PayPal and describe the data. In Section III we estimate a conventional gravity model and report results. In Section IV we estimate the parameters relevant to Chaney’s theory in the PayPal data and test the model’s central prediction in that context. In Section V we estimate merchant-level regressions that link the scale and geographic scope of merchants’ sales on the platform to the age of their accounts. Section VI concludes.

Section II. Data
Our proprietary, anonymous, and aggregated data were provided by PayPal, an online platform that processed 6.1 billion transactions in 2016, transactions that were valued at $354 billion (PayPal, 2017). PayPal enables business and non-business sellers and buyers to send and receive payments over the internet. PayPal provides its users with a digital wallet that is linked to payment instruments such as credit cards, debit cards and bank accounts. In 2016, PayPal hosted 197 million customer accounts, a figure that includes 15 million accounts held by merchants (PayPal, 2017). These figures are the outcome of a remarkably fast growth process; the firm was only founded in December 1998.

The proprietary, anonymized and aggregated data that PayPal provided to us represent a draw of all transactions that occurred on the platform within 24 individual days in the calendar year 2016. Each payment-receiving merchant in the dataset has a unique, but anonymized, identification code. Before delivering the data to us, PayPal aggregated these data up to produce observations at the level of payment-receiving-merchant by payment-making-region. The data report the number of PayPal transactions and the total USD value of payments that were sent from each iso2 region to each merchant in the 24-day

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13 See “What is PayPal and how does it work?” at the Paypal website. It is noteworthy that some Paypal transactions take place over online marketplaces (such as eBay), while others are directly made through a website without a marketplace intermediary.
14 We compare the activities of Paypal merchants to those of firms in the broader literature on international trade. PayPal’s 15 million merchant accounts would include those of charities and other entities that receive payments, but are not for-profit firms.
15 A brief timeline of key events in Paypal’s history is available in O’Connell (2020).
16 The sampled dates were the 7th and 22nd of each month, a pairing that was chosen to avoid major holidays. The data do not include peer-to-peer payments on Venmo, a company that is owned by PayPal, or any of PayPal’s other subsidiary companies.
17 We lack similar identifying information on the individuals or firms that make the payments. Payments made with these accounts are aggregated up the level of an iso2 region.
18 Rather than at the level of sovereign countries, the data are reported at the level of iso2 region, which means that entities such as Greenland and Puerto Rico appear separately in the data. Each merchant in the sample is assigned to a single iso2 payment-receiving region for the purposes of reporting these data. We view the additional detail as useful for understanding the geography of payment activity, and retain iso2 regions as the spatial unit of study.
sample period of 2016. Because data are reported for individual payment-receiving merchants that are matched to specific iso2 codes, we are able to construct a bilateral count of the number of merchants in an iso2 region receiving payments from each iso2 region.

When aggregated across payment-receiving merchants, the data offer a consistent measure of payment activity within each iso2 region as well as between them. We use the iso2 information to merge with standard bilateral gravity data from the French research institute Centre d’Études Prospectives et d’Informations Internationales (CEPII). We use the \textit{distw} measure of bilateral distances from these data.\footnote{The various distance measures in the CEPII data are distinguished primarily by their treatment of domestic distances. CEPII’s \textit{distw} variable calculates internal distances as a population weighted average distances between cities in each region. See Mayer and Zignago (2006) for more detail on the CEPII distance measures.} For our top-level gravity model we construct a HOME dummy variable that takes the value of one for flows within an iso2 region.

The data are collected electronically and on a comprehensive basis, so they required very little in terms of cleaning. We removed the small number of merchants that were associated with two iso2 regions.\footnote{Some merchants were assigned to both the United States and Puerto Rico. We removed U.S.-Puerto Rico payments (in both directions) from the sample to prevent this data coding issue from affecting our conclusions.} We initially undertake gravity regressions that include intra-regional payments, but exclude these in subsequent analysis focusing on the geography of international payment activity.

For our subsequent exercises, we impose a lower limit on the value of firms’ total international sales receipts – in our analysis we restrict the sample to firms that earn at least $10,000 in sales within our 24-day data sample.\footnote{When pro-rated to annual flows, this restriction implies that the smallest merchants would have annual export sales of approximately $150,000. Most PayPal merchants are involved in retail trade, which means that $150,000 in gross export sales does not necessarily imply that a merchant is large in terms of net income.} There are three reasons to truncate the sample in this way. First, the sample truncation mimics Chaney (2018), who restricts the sample of firms he studies to those with exports of at least $200,000 because his theory relates to firms in the upper tail of the firm-size distribution. Second, the sample restriction limits the influence of PayPal’s legacy role as the payment mechanism for eBay. Relatively small merchants on eBay and other marketplaces (e.g., hobbyists or collectors) are unlikely to have followed the same growth trajectories as standard PayPal merchants, and therefore prove a poor fit for comparisons with conventional firms engaged in international trade. Finally, our sample truncation should reduce the role of sampling error in determining the scale of merchants’ exports. Since the data are taken from only 24 days of activity, infrequent traders that appear in the sample by chance would appear artificially large in these data. Our results are not substantially different if we remove the threshold and apply the same techniques.

\footnote{We shall typically refer to the value of payments received as “sales,” and when tracking payments between iso2 regions refer to these sales as “exports” or “international sales.”}
The merchant-level data also report the date in which each merchant opened an account on PayPal. We use this data to construct a merchant-level variable that measures the account’s age, in discrete years, in 2016. We use these data in our final regressions in Section V that study the effects of account age on the scale and geographic scope of merchants’ exports in 2016. A small proportion of merchants have accounts that were opened in 1999; we drop these merchants from the regressions because the number of 1999 accounts is small and these accounts do not cover an entire year of merchant entry. We also drop from the regressions data on accounts that report the year of account creation as 2017, even though we observe transactions that occur for these firms in 2016.  

Summary statistics
In Table 1 we report summary statistics for each of three aggregations of the 24-day data sample: 1) aggregate flows between regions, including intra-regional flows; 2) merchant-by-destination sales data; and 3) merchant-level data on total inter-regional sales activity, an aggregate of the data in 2). We report the value of sales and the number of transactions for each aggregation of the data, as well as the ratio of sales value to transaction numbers. For bilateral pairs we also report summaries of the number of merchants selling along a route, the number of transactions per merchant, and summaries of the data on distance and the Home dummy variables. At the merchant level, we also report summaries of the average distance of export sales, the average squared distance of export sales, the number of destination markets reached, and account age. For each variable we report the number of observations (N), the minimum value, the value at the 95th percentile, the median, the mean and the standard deviation.  

The first row of Panel A of Table 1 shows the distribution of bilateral payment values across all bilateral iso2 corridors. There is wide variation in these aggregates, from $0.01 at the minimum value to $3.1 million at the 95th percentile. There is a strong rightward skew in these data; the average value of bilateral payments is more than $6.5 million, but the median is just $5,271. Row 2 reports statistics for transaction activity, which also has a strong rightward skew. The mean number of transactions for a bilateral pair is 117,175, while the median is just 71. Row 3 shows that the distribution of the number of merchants selling to an iso2 code is also strongly right skewed, with the mean iso2-region pair served by 331 merchants, while the median is only 10.5.

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23 We treat this as a reporting error, though it may reflect some anachronism of which we are unaware about how account creation dates are reported or recorded.

24 We report the 95th percentile rather than the maximum value so that it is impossible to use our results to infer the identity of any individual merchant. The fact that the summary statistics are calculated from a 24-day sample of payment activity, rather than annual totals, further thwarts any effort to infer the identity of a specific merchant. We report the 95th percentile, rather than the max of iso2-level statistics, in order to be consistent.
Rows 4 and 5 show statistics for two ratios constructed from the previous three variables. Row 4 reports the average value per transaction, which is calculated by taking the ratio of total payment value to total transactions for each bilateral pair. The key lesson is that PayPal transactions are typically quite small, as international transactions go. For the median iso2 pair, the average value per transaction is just $58, and the mean is just $100. The median number of transactions per merchant on a bilateral route is approximately 6, while the mean is 74. Approximate annualized figures for these data can be calculated by multiplying by 15, which would mean that the median number of transactions per merchant on a bilateral route would be just under 90.

The distance variable in the region-to-region bilateral payments data has a mean of 7,625 km and a median of 7,733 km, indicating very little skewness. High median and mean distances indicate that PayPal transactions occur on a large number of long-distance routes. Only one percent of the bilateral aggregates represent payments that occur within an iso2 code.

Panel B reports summary statistics for data aggregated to the merchant-by-destination region level. These statistics reveal, once again, strong rightward skew in payment value and in transaction numbers. The value-per-transaction variable is once again dominated by small values. The median value per transaction for merchant-by-destination region pairs is just $97, while the mean is $256.

Panel C reports summary statistics for an aggregation of the merchant-by-destination data up to the level of the payment-receiving merchant. Once again, the distribution of sales activity is strongly right skewed. The merchant at the median received $31,355 in payments during the 24-day sample, while the average merchant received $268,000. There is also a wide distribution of merchants’ receipts on the platform. The merchant at the 95th percentile of the distribution received payments that were more than 53 times larger than the smallest merchants remaining in the truncated sample. The median number of international transactions per merchant was 128, while the average is 5,099. The median value per transaction at the merchant level is $295, while the mean is $604.

The distance measures reported in Panel C are functions of value-weighted average distance of merchants’ international PayPal sales. We report both the value-weighted average distance itself, and the value-weighted squared distance, since both variables are used in subsequent sections. Neither distance variable is strongly skewed. The data show that the merchants in our sample typically export over long

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25 For context, note that in international goods trade data, Hornok and Koren (2015) show that the median value of an export shipment from the United States is $14,467 and from Spain $13,234.
26 In international goods trade Hornok and Koren (2015) report one shipment per month at the median, and shipment in two months of the year.
27 Table 1 summarizes the data for the set of iso2 pairs where payment activity is observed.
28 These data and the data summarized in Panel C only contain transactions from merchants with at least $10,000 in sales during the sample period.
distances. The median value-weighted average distance of export sales is 8,133 kilometers, which is almost exactly the distance from London to Beijing. Half of the merchants in the sample would have average distances of export sales larger than 8,133 kilometers. The data also reveal that most PayPal merchants serve many different foreign markets. The median merchant serves 17 international markets within the 24-day data sample, while the mean number of markets served is 23.6.  

The account age variable ranges from 0 to 16, reflecting the age of merchants’ accounts (among accounts created during 2000-2016). The median merchant has an account age of 6 years and the average account age is 6.5 years. Unreported results show that net annual growth rates of merchant numbers, as reflected in the 24-day sample, were reasonably stable over the 16 years of account creation.

The key lessons from the summary statistics are the following: First, the PayPal data are composed primarily of small transactions; several measures of central tendency put the typical transaction value in the low triple digits. This reflects the nature of PayPal’s clientele, who are engaged in retail or other activities associated with relatively small-value transactions. Second, the median merchant is also somewhat small, in terms of its PayPal activity, receiving just 128 international payments during the 24-day sample period, or 5.3 transactions per day. Third, the typical PayPal merchant’s export activity covers vast distances; a majority of merchants serve 17 or more foreign markets within the 24-day period. Despite the relatively small scale of most merchants’ activity on the platform, the geographic scope of their sales is immense. The median merchant’s average export distance is 8,133 km. This portrait of export activity on the platform is vastly different to what is commonly known from studies of exporting firms in conventional data; that literature finds that most firms sell to a small number of markets, markets that are usually geographically proximate. In subsequent sections of the paper we investigate further the geography of international sales activity on PayPal, and ask whether geographic frictions impose differential burdens on PayPal merchants of different sizes.

Section III. An empirical gravity model of payments on the platform

In this section we estimate an empirical gravity model to better understand region-to-region sales accomplished with PayPal. Gravity models are a conventional tool for understanding data like ours, which document bilateral variation in international payment activity. Our data also allow us to construct the number of international transactions and the number of merchants receiving payments for each origin-

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29 Eaton, et al. (2004) show that in French manufacturing data for 1986, 34 percent of exporting firms served only one foreign market, and only 20 percent of firms served 10 markets or more.

30 In data documenting conventional international trade in 1986, Eaton, et al. (2011) find that 17,699 (52 percent of) French exporting firms export to Belgium, while only 43 firms export to Nepal.
destination pair. Our primary interest is in the distance elasticity of these three outcome variables, but in our initial regressions we also include a dummy variable to quantify home bias.

We estimate a standard form of the empirical gravity model of trade, but we replace the value of bilateral trade with the value of bilateral payments on the PayPal platform in our data sample. The empirical model relates bilateral payment activity between two countries to geographic variables that are important in empirical models of international trade. Following Santos Silva and Tenreyro (2006), we adopt a specification that uses the Poisson Pseudo Maximum Likelihood (PPML) estimation procedure. Formally, the estimation model takes the form:

\[ V_{ij} = \exp\{\alpha_i + \alpha_j + \beta \ln \text{Dist}_{ij} + \gamma \text{HOME}_{ij}\} + e_{ij} \]  

where \( V_{ij} \) is the total value of payments region \( j \) makes to region \( i \); \( \alpha_i \) and \( \alpha_j \) are fixed effects that capture total levels of payments received by region \( i \) and payments made by region \( j \), respectively; \( \text{Dist}_{ij} \) is the distance between \( i \) and \( j \), \( \text{HOME}_{ij} \) is a dummy variable indicating that the trade flow is internal to a region, and \( e_{ij} \) is a Poisson error term. The key coefficient of interest is \( \beta \), which measures the elasticity of payment activity to distance. The \( \gamma \) coefficient measures the excess intensity of domestic payment activity relative to international payments. In subsequent regressions we replace the payment value variable \( V_{ij} \) with the number of transactions on a bilateral link and with the number of merchants in \( i \) that receive payments from \( j \).

Column 1 of Table 2 reports results from an estimation of equation (1) using bilateral payment value on the left-hand side. The estimated distance coefficient in this regression is -0.58, which implies that a 10 percent increase in distance reduces bilateral payment value by 5.8 percent. This distance coefficient is substantially smaller than is typically estimated in international trade data. Disdier and Head (2008) conduct a meta-analysis of 1467 estimates in 103 empirical papers on the gravity model of trade, and find a mean distance elasticity of -1.31.

The estimated distance elasticity of PayPal payments is comparable in magnitude to those estimated for international data from eBay (Lendle, et al. 2016) and Mercado Libre (Hortacsu, et al. 2009). In a different sample of international eBay transactions, Lendle, et al. (2013) estimate a much larger distance elasticity, -1.50. Estimates of the distance elasticity in domestic transactions on the online marketplaces range from -0.41 (Fan, et al. 2018, AliBaba transactions within China) to -0.07 (Hortacsu, et al. 2009, eBay transactions within the U.S.).

31 Head and Mayer (2013) offer a kernel density graph of 1,835 distance elasticities estimated with the gravity model, and note that the central tendency is in the neighborhood of -1.

32 In another paper that relates to ours, Agarwal, et al. (2020) conduct a study of detailed credit card transactions in 2003, a time when internet transactions were likely to be a much smaller share of the sample. The object of their study is a payment technology, like ours, although the transactions they study are very much linked to the travel.
Column 1 also reports the coefficient on the Home dummy variable. This coefficient estimates the excess intensity of sub-national payments, which is sometimes known as home bias. Our data report both domestic and international payments across the globe, which means that ours is an unusually rich and detailed data set for exercises of this kind.\textsuperscript{33} The Home dummy coefficient represents the cross-country average home bias across all regions in the sample. The estimated coefficient of 2.13 on the home dummy variable suggests that, after controlling for distance, the value of transactions within iso2 regions is, on average, \(e^{2.13} - 1 = 7.41\) times larger than value of transactions between them.\textsuperscript{34} This estimate of home bias for domestic PayPal payments is roughly in line with relatively recent estimates of home bias in U.S.-Canada trade flows.\textsuperscript{35}

We report the home bias estimates, but are reluctant to draw strong inferences about them, because some countries restrict, or even prohibit, the use of PayPal for domestic transactions. For example, although Chinese merchants were able to use PayPal to serve foreign markets, PayPal did not have a license for domestic transactions within China until 2019. Countries in the sample with relatively few, if any, domestic transactions as a result of such restrictions will tend to bias downward our average home bias estimate.\textsuperscript{36} Standard interpretations of national home bias are also sensitive to critiques that aggregation over poorly-measured domestic distances is an important source of bias.\textsuperscript{37} Estimates in subsequent sections of the paper use data that excludes domestic transactions.

In addition to data on the value of bilateral payments, our data contain information on the number of transactions and the number of merchants receiving payments along a bilateral route. We replace

\begin{itemize}
\item habits of the card holder. They estimate a distance elasticity of -1.051 in their data. In our data transactions are much less likely to require the physical presence of the purchaser in the seller’s location, which is a key reason that distance should be much less important for PayPal transactions.
\end{itemize}

\textsuperscript{33} Most studies of international trade lack consistent data on domestic activities, or have such data for a very limited number of countries. Some studies use the World Input Output Database (Timmer, \textit{et al.} 2015), which report imputed values of domestic flows. Our data report actual transactions for both domestic and international payment activities.

\textsuperscript{34} Anderson and van Wincoop (2003) argue for counterfactual analysis consistent with their particular theory of gravity, which is a general equilibrium theory with iceberg trade costs that is a poor fit for these data. The exponential calculation used here is more transparent, and less reliant on untested assumptions about second-order responses to border removal.

\textsuperscript{35} Suvankulov (2016) applies a PPML specification to updated data like those in the initial McCallum (1995) study, and find a border effect estimate of 9.0 for Canada. In unreported regressions we interact a Canada dummy with the home dummy and include the interaction along with the home dummy in order to calculate a Canada-specific value of home bias for purposes of direct comparison. Home bias in Canada is slightly larger than for the global average. We estimate an implied home bias of \(e^{10.0} - 1 = 10.0\).

\textsuperscript{36} We thank Usman Ahmed of PayPal for drawing our attention to this issue.

\textsuperscript{37} Hillberry and Hummels (2008) show that estimated U.S. state border coefficients are highly sensitive to the level of aggregation in the underlying data. Coughlin and Novy (2019) explore this issue theoretically and empirically. Hortacsu, \textit{et al.} (2009) show an excess intensity of very local transactions in data on domestic eBay transactions. It is quite likely that nonlinear effects like these are present in our data, which complicates interpretation of the Home dummy coefficient.
payment value in equation (1) with these two variables. These estimates appear in columns 2 and 3 of Table 2.

The effect of distance and borders on transaction numbers is roughly in line with that of the value of payments, though transaction numbers are slightly more sensitive to distance and slightly less sensitive to borders than is payment value. In broad terms, the similarity of the coefficient estimates in the regressions using transaction numbers and payment value suggests that mean transaction sizes (i.e., average values per PayPal transaction) are reasonably stable over geography. The fact that transaction numbers are slightly more responsive to distance than is payment value suggests that the average value of an international PayPal transaction rises slightly with distance.\footnote{Following Hillberry and Hummels (2008), we apply decomposition methods and undertake log-linear ordinary least square (OLS) regressions using the variables in Table 2. Focusing on ratios of the variables, we find that the distance elasticity of average payment value is 0.085, meaning that each log point increase in distance raises the mean transaction value by a modest 8.5 percent. One explanation for average transaction values rising with distance would be that the transportation costs of moving goods associated with a purchase rise with distance, which makes smaller transactions somewhat less economical over long distances. The estimated coefficient on the home dummy is also negative, indicating that average transaction sizes are smaller when transactions occur within an iso2 region. OLS regressions in the manner of Hillberry and Hummels (2008) show that the number of transactions per merchant falls with distance. The intensive margin of transactions per merchant explains 45 percent of the elasticity of distance on transaction numbers and 60 percent of the effect of the home dummy on transactions. The lesson is consistent with that of the PPML regressions; the extensive margin of merchant activity represents only a portion (roughly half) of the overall effect of geography on export sales.} In a study of credit card purchases, Agarwal, et al. (2020) also find that longer distance transactions are larger than those over shorter distances.

The pattern of merchant participation across bilateral markets, however, is noticeably different. Column 3 of Table 2 shows that the elasticity of the number of merchants receiving payments to bilateral distance is only -0.31, which means that a ten percent increase in bilateral distance only reduces the number of merchants receiving payment by 3.1 percent. Average home bias is only $e^{0.77} - 1 = 1.16$. There is virtually no measured home bias at all for the merchant-participation margin. The primary lesson from Column 3 is that the firm extensive margin appears to play a much less pronounced role in explaining the response of PayPal payment values to geographic frictions than it does for conventional international trade.\footnote{OLS regressions in the manner of Hillberry and Hummels (2008) show that the number of transactions per merchant falls with distance. The intensive margin of transactions per merchant explains 45 percent of the elasticity of distance on transaction numbers and 60 percent of the effect of the home dummy on transactions. The lesson is consistent with that of the PPML regressions; the extensive margin of merchant activity represents only a portion (roughly half) of the overall effect of geography on export sales.} In firm-level data on conventional US exports Bernard, et al. (2007) estimate a distance elasticity of the firm extensive margin of 1.14, and find that this margin accounts for 84 percent of the total distance elasticity of payment value.

The two key lessons that we take from the estimates in Table 2 are, first, that the elasticity of payment value is considerably lower in PayPal data than in conventional international trade data, and, second, that the firm extensive margin accounts for a much smaller share of geographic variation in sales activity on the PayPal platform than it does in conventional international trade data. A better understanding of how these two phenomena might be linked requires a theory, preferably a theory with
estimable parameters that can inform the interpretation of our data. The recent gravity theory of Chaney (2018) appears to be the most useful for our purposes.

Section IV. Application of Chaney (2018)

In our next set of exercises, we interpret the PayPal data using a recent theory of the gravity relationship in international trade proposed by Chaney (2018). Standard general-equilibrium theories of bilateral trade model the entire universe of foreign sales, with consumer choices determined by relative differences in the delivered price of an item. Relative prices vary because of iceberg trade costs. Our data represent only a small fraction of all international payment activity – the activity that appears on the PayPal platform itself. Iceberg trade costs also seem inappropriate in the context of purchases on the internet, which may include digital goods, for example. Absent a fully developed model of endogenous choice of a payment technology, and absent comparable data on transactions concluded with other forms of payment, Chaney’s theory seems most appropriate for analysis of our data. The model offers novel and important insights regarding the interpretation of the distance elasticity in gravity models of international trade.

As Chaney (2018) explains, existing theoretical gravity models of trade are overly prescriptive – in terms of the form of international trade costs that are assumed, the production technologies that are assumed to be available to firms, and in the nature of the assumed choices that consumers make in the model. He shows that a gravity-like trade pattern will emerge if the scale of firms’ export sales activity is positively correlated with the geographic scope of that activity. In particular, his theory assumes a Pareto distribution of firm sizes and a tendency for larger firms to sell over longer average distances. Chaney’s theory generates a functional form that relates the distance elasticity of trade to two underlying parameters: the shape parameter of the Pareto distribution of firm sizes, and the parameter that defines the link between the scale and geographic scope of firms’ export sales. When the Pareto distribution is parameterized to produce Zipf’s Law, the predicted distance elasticity of international trade approaches its commonly observed value, -1.

The Chaney framework is useful for this paper for at least three reasons. First, the framework is more general than other theories of gravity – theories with microeconomic underpinnings that are not well-suited to interpretation of our data. Second, Chaney proposes additional empirical exercises that can be used to explain differences between the gravity estimates from the PayPal data and those from the literature studying conventional international trade. Particularly useful is a regression that measures the strength of the relationship between the scale of a firms’ export sales and the geographic scope of those

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40 Chaney (2018) also provides empirical results for data tracking conventional exports by French firms. We compare our results to those in order to illustrate the differences between our data and data representing trade under conventional methods for making payments in international commerce.
sales. Finally, our data offer an early opportunity to apply Chaney’s estimation procedure to data outside the specific context of conventional French exports. Our globally consistent data on international PayPal payments give us an opportunity to estimate outcomes for several large countries, and to learn from comparisons between them.

**Approach to estimation**

We follow Chaney’s approach to estimation in order to make the link to his work transparent. He conducts two empirical exercises with firm-level data, and then conducts a country-specific gravity regression using French export data. We follow the same steps, using merchants’ international PayPal receipts from eight countries – Australia, Canada, China, France, Germany, India, Japan, and the United States. We also estimate Chaney’s three structural parameters in the global PayPal data, aggregating across countries or pooling country-level data, as seems most appropriate.

Because the underlying mechanisms in Chaney’s theory relate to stable processes for firm growth, and because the growth rates of small firms’ exports are often unstable, Chaney trims the distribution of firms’ export sales from below, constraining his estimates to those firms with at least $200,000 in annual export sales. Within the trimmed sample, he groups firms into bins, with firms of approximately the same value of export sales put in the same size bin. We follow both of these steps: We first limit the sample to firms with more than $10,000 in total international receipts during the 24-day sample. We then follow Chaney’s approach to constructing firm-size bins. These size bins are the unit of observation in the first two empirical exercises.

In order to construct the size bins, we calculate values of the minimum and maximum values of merchants’ total international PayPal sales within each export country. We then partition this range into 50 bins of equal log width. Within each bin \( b \), we calculate the within-bin average of firms’ international receipts, which is given by

\[
K_{ib} = \frac{\sum_{i} \sum_{j} x_{ij} I (r \in b)}{\sum_{i} I (r \in b)}, \tag{2}
\]

---

41 As will become apparent, Chaney’s methods require a large number of payment-receiving firms within a country in order to be useful. These eight countries have large numbers of payment receivers, and were further chosen because they represent considerable diversity in terms of geographic location and levels of per capita income. We also estimate results from the UK and Hong Kong, but do not report them for reasons of space. UK results are similar to those from France and Germany, though UK exports are more sensitive to distance. Hong Kong has a relatively small number of PayPal firms in our data, and parameter estimates that are similar to those of the developed countries we study. Hong Kong’s distance elasticity of international PayPal sales is quite low, and is most similar to the value reported for Canada.
where \( i \) is the region or country being studied, \( b \) identifies the size bin, \( r \) is a payment receiver (i.e., a firm), \( V_{ij} \) is the value of payments received from region \( j \) by receiver \( r \) in region \( i \), and \( 1[r \in b] \) is an indicator that the payment receiving merchant is a member of size bin \( b \).

Under the Pareto distribution, the fraction of payment-receiving firms \( r \) that receive payments larger than \( K_b \) takes the value:

\[
1 - F(K_b) = \frac{\sum_{j=0}^{\infty} 1[r \in b']}{\sum_{j=1}^{\infty} 1[r \in b']}.
\]  

(3)

In order to parameterize Zipf’s law, like Chaney, we estimate

\[
\ln[1 - F(K_b)] = a - \lambda \ln(K_b) + \epsilon_b,
\]

via OLS. The \( \lambda \) parameter defines the shape of the Pareto distribution of the value of merchants’ international sales. Zipf’s Law implies that \( \lambda = 1 \).

Chaney posits that an important reason for the growth of firms’ international sales activity over time is an improving ability to accomplish sales in more distant geographic markets. This hypothesis amounts to an empirical prediction that firms with higher export volumes will also sell over longer average distances. The specific mathematical relationship in Chaney’s theory focuses on a link between the total value of firms’ export sales and the average squared distance of their export sales.\(^{42}\) The average squared distance of payments received among merchants in bin \( b \) is given by

\[
\Delta(K_b) = \sum_j (Dist_{ij})^2 \left( \frac{\sum_{r \in b} 1[V_{ij} > 0]}{\sum_{r} \sum_{j} 1[V_{ij} > 0]} \right).
\]

(5)

The elasticity of squared average distance to total export sales value is estimated with the equation

\[
\ln\Delta(K_b) = a + \mu \ln(K_b) + \epsilon_b,
\]

using OLS. Once again, the unit of observation is a merchant size bin. \( \mu > 0 \) indicates that merchants with more total international sales sell a relatively larger proportion of those sales over larger distances. Larger values of \( \mu \) indicate a stronger link between the size of firms’ international sales and the average distance of those sales.

Chaney also estimates a form of the gravity model. The theory is predictive of the pattern of trade for an export country, and so he estimates a country-level gravity model for French exports. Variation in total import demand is controlled directly – the value of imports (from all sources) is included as a control variable.\(^{43}\) The estimating equation is as follows:

\[
\ln(V_{ij}) = \theta_i - \zeta \ln(Dist_{ij}) + \eta \ln(imports_j) + \epsilon_{ij}.
\]

(7)

\(^{42}\) The use of squared distance as the measure of distance relates to the fact that the mathematics Chaney employs is tied to power laws. The exponent on distance is related to the rate of growth of sales, which is also characterized by exponential growth.

\(^{43}\) Chaney’s inclusion of the total value of destination-country imports in the regression is intended to control straightforwardly for the inward multilateral resistance variable, as described in Anderson and van Wincoop (2003).
which is also estimated via OLS. The coefficient of interest is $\zeta$, the elasticity of payment value to distance. Empirically, Chaney estimates equation (7) using data on trade flows that surpass a certain minimum distance, 2,000 km. We also estimate (7) with a sample of observations with bilateral distances that exceed 2000 km.

Results from the Chaney regressions

The first parametric assumption of the Chaney theory is that firms’ export sales should follow Zipf’s law, an empirical regularity in which the $\lambda$ parameter in equation (4) takes the value of 1. Chaney estimates equation (4) on French firm level export data, and reports an estimate of $\lambda = 1.00$. We apply Chaney’s approach to estimating $\lambda$ to our data on international PayPal transactions, reporting results for eight individual countries that are relatively large in terms of overall PayPal sales activity. The results of these exercises are reported in Table 3, Columns 1 through 8. The country-level results in Table 3 are ordered, from left to right, to reflect the decreasing number of merchants appearing in each country’s sample. The estimates of $\lambda$ for China and the United States satisfy Zipf’s law, as can be seen in Columns 1 and 2. Columns 3 through 8 report results for additional countries, with estimates of $\lambda < 1$ for developed countries and $\lambda > 1$ for India. Column 9 reports $\lambda = 0.97$ for the global distribution of merchants’ international sales. For purposes of comparison, Chaney’s regression results from the French export data are reported in Column 10.

Our tentative interpretation of the results in Table 3 is that Zipf’s law holds for international PayPal payments, so long as the data contain a sufficiently large number of merchants. The standard explanation for Zipf’s law is that it represents an emergent steady state that follows from a stochastic growth process that is stable across the firm-size distribution. Growth in PayPal payments is driven by fast-growing e-commerce, and these payments represent only one of several payment mechanisms used on the internet. The assumption of a growth process that is stable, both over time and across the firm-size distribution, might therefore not seem appropriate. Moreover, the novelty of the PayPal payment platform – all the merchants we study joined the platform in only a 16-year period – casts doubt on the proposition that data from the sixteenth year would represent a steady state. Nonetheless, it does appear that Zipf’s

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44 If one takes Zipf’s law as a benchmark, the estimates suggest that the largest PayPal exporters in the developed countries are disproportionately large, while the largest merchants in India are too small, relative to the distribution of Indian merchants’ export sales.

45 This is an aggregate estimate, not a pooled cross-country average. Using the global distribution of merchants with export sales of at least $10,000, bin sizes were calculated as in Chaney (2018), and equation (2) was estimated using the global merchant-size bins as units of analysis.

46 See Gabaix (1999) for a discussion in the context of city sizes.
Law holds on the platform, for the distributions of Chinese and US firms, and (approximately) for the global distribution of PayPal merchants’ exports.  

Empirical studies of firm export growth using conventional international trade data show that firms typically begin exporting by entering nearby markets, only later enter more distant markets. Slightly different work with the same implications shows that in the cross-section, firms with larger values of total exports tend to sell to more markets and to more distant markets. Chaney’s theory describes the mathematics of growth processes that produce the cross-sectional outcome, and proposes an empirical test using cross-section data. Using equation (6), he estimates a relationship between the value of firms’ export sales and the (value-weighted) squared average distance of firms’ sales. The parameter that defines this conditional correlation in his theory, \( \mu \), takes the value of 0.11 in data on French exports.

The key results of this paper appear in Table 4, which reports estimates of \( \mu \) in the PayPal data. Estimates from individual countries and from a pooled regression all indicate that the relationship between a merchant’s scale and the geographic scope of its exports is much weaker in PayPal data than Chaney observes in conventional international trade data from France. Country-level point estimates for \( \mu \) range between -0.01 and 0.08 in the PayPal data. A pooled regression over the global sample with country-level fixed effects produces a global average estimate of \( \mu = 0.02 \). The low estimates of \( \mu \) in PayPal data indicate that exports of relatively small PayPal merchants cover average distances that are nearly as large as the distances travelled by the export sales of much larger PayPal merchants. The implication is that distance poses much less of a relative burden on smaller merchants in PayPal data than it does for small firms in conventional international trade data.

Although Chaney’s mathematical conditions are intended to be general to a wide variety of micro-foundations, Chaney (2018) proposes a network model that may be useful for understanding the differences between conventional and online commerce. In the model, firms’ initial search for counterparties is constrained to a defined geographic area surrounding the firm. Once the firm locates a counterparty within the initial search area, it becomes able to search in the vicinity of that counterparty, as well as in its own vicinity. The geographic scope of the firm’s future sales thus depends upon its previous sales, and overall sales growth depends upon a gradual expansion of the geographic scope of the firm’s sales. In this framework, a key reason the internet would act to reduce the distance elasticity of sales is by

47 It seems likely that, as more merchants join PayPal, and as international sales of existing PayPal merchants grow, the distributions of merchant sales in countries with fewer exporters will also converge to Zipf’s law, though this is a hypothesis that we cannot test in 2016 data alone.


49 See, for example, Eaton, et al. (2004) and Boitier and Vatan (2017).

50 It may be that the weaker relationship between firm scope and firm scale is not specific to PayPal, but rather a feature of e-commerce more generally. Confirmation of this hypothesis would require access to data from other e-commerce firms.
dramatically expanding the scope of the firm’s initial search. The less constrained is the search for the initial counterparty, the weaker the relationship between the scale of firms’ sales and the average distance of those sales. At the limit, if the initial search is geographically unconstrained, there will be no relationship between firms’ scale and geographic scope. It seems likely that the internet alleviates most geographic constraints, which would substantially weaken Chaney’s proposed relationship between scale and geographic scope, represented by the parameter $\mu$.

The purpose of the Chaney model is to explain the persistence of a large negative distance coefficient in the gravity model, specifically an estimate that approximates -1. In Table 5 we report results from country-level gravity regressions that apply Chaney’s OLS estimation procedure to the PayPal data. Columns (1)-(8) report gravity model estimates for export sales from individual countries on the PayPal platform. Only Japan has a point estimate of the distance elasticity with a magnitude greater than one, though the null hypothesis of unitary distance elasticities in Germany’s and Australia’s samples cannot be rejected. In general, we find a much weaker effect of distance on bilateral PayPal sales than is common in conventional international trade; column 9 shows that the pooled OLS estimate of the distance elasticity across all exporting countries is -0.70 in the PayPal data. Two countries of particular interest are China and the United States, since the estimates in Tables 3 and 4 indicate that these countries’ estimates of $\lambda$ and $\mu$ are consistent with the parametric restrictions that underlie Chaney’s theory. The estimated distance elasticity of -0.4 in U.S. sales is much smaller in magnitude than -1. The estimated distance elasticity of China’s PayPal exports is, in fact, positive, which contradicts Chaney’s specific theory, as well an enormous empirical literature on bilateral trade flows.51

Testing the Chaney theory
Our primary reason for employing the Chaney (2018) theory to estimate the $\mu$ parameter that measures the relationship between merchants’ export scale and the geographic scope of those exports. Our data also offer us an opportunity to test the theory’s central prediction, which relates to the magnitude of the distance elasticity of trade ($\zeta$). Under certain conditions on $\lambda$ and $\mu$, Chaney’s Proposition 1 predicts that a particular non-linear function of these two parameters predicts the magnitude of $\zeta$. Chaney also offers a subsequent, more specific prediction: that Zipf’s law in the firm size distribution causes $\zeta$ to approach the

51 This highly unusual result might be best understood as a result of spatial competition among digital payment platforms. Most transactions in China would occur on AliBaba or other Chinese electronic payment systems. Chinese transactions involving other East Asian countries might also use those platforms. Chinese firms appear to use PayPal to sell to customers in markets where PayPal use is more common (e.g. Europe and North America). China’s PayPal exports to other Asian countries are relatively small, so there is no tendency in the Chinese data for payments to fall with distance. Indeed, the regression coefficient in Table 5 indicates just the opposite, that the value of payments to China is increasing - rather than decreasing - in distance.
value of 1. Chaney finds evidence consistent with these predictions in data on conventional exports from France. We ask whether these predictions hold up in our data.

Because our data represent only those transactions that occurred on the PayPal platform, this exercise should not be seen as an explicit test of Chaney’s theory as it results to the entirety of international trade. Nonetheless, in some cases the estimated values of $\lambda$ and $\mu$ satisfy the preconditions of Proposition 1. Our results can thus be understood as a test of whether those conditions are sufficient for predicting $\zeta$. Alternatively, one can view these exercises as a test of the proposition that Chaney’s theory accurately describes the evolution of sales on the PayPal platform itself.

Following Chaney (2018), we evaluate parameter uncertainty using 10,000 bootstrapped estimates of each regression. We evaluate the theory in two ways. First, we evaluate parametric restrictions that are necessary conditions for the Chaney’s mathematical prediction of the distance elasticity of trade. Second, we evaluate the prediction itself.

Chaney’s mathematical derivations are built on three parametric restrictions: a) $\lambda \geq 1$; b) $\mu > 0$; and, c) $1 + \mu \geq \lambda$. The first parametric condition establishes that the heterogeneity in the firm size distribution is not too large. The second condition requires that larger firms sell a relatively larger share of their sales in distant markets than do smaller firms. The third condition restricts the joint growth processes so as to ensure a stable solution.

Proposition 1 in Chaney (2018) indicates that if the parameter restrictions in (a), (b) and (c) hold, then the distance elasticity of trade, $\zeta$, asymptotically approaches

$$\zeta = 1 + 2 \frac{(\lambda - 1)}{\mu}. \quad (8)$$

Under Chaney’s theory, the distance elasticity of trade approximates unity because the second term on the right-hand side is approximately zero. The size of the second term is constrained for two reasons. First, Zipf’s law implies an estimate of $\lambda$ that is approximately 1, which pushes the numerator toward zero. Second, the effect of any deviation from Zipf’s law in standard international trade data is mitigated by a sufficiently large estimate of $\mu$ in the denominator. Chaney estimates $\lambda = 1.0048$ and $\mu = 0.11$, parameter values that – using equation (8) – generate a predicted distance elasticity of $\zeta = 1.086$. The fitted value of $\zeta$ from equation (8) is statistically quite close to Chaney’s gravity model estimate of $\zeta = 1.09$, and Chaney therefore accepts the hypothesis that equation (8) accurately predicts $\zeta$.

The nonlinearity of equation (8) means that if $\lambda$ strays away from unity and $\mu$ approaches zero, the predicted value of $\zeta$ becomes highly variable. The point estimates of $\zeta$ in Table 5 do indeed vary considerably across countries. But more importantly for the purposes of hypothesis testing, parameter uncertainty around $\lambda$ and $\mu$ can generate wide standard errors for $\zeta$, even in cases where the point estimates for $\lambda$ and $\mu$ are consistent with parameter restrictions (a)-(c). Bootstrap draws for which $\mu \cong 0$
magnify the effect of any deviation of $\lambda$ from unity, and cause the predicted variance of $\zeta$ to explode. This is an issue in the PayPal data, where the estimated value of $\mu$ is often in the neighborhood of zero.

We test Chaney’s parametric restrictions and his prediction for the distance elasticity of trade. We do so for the eight countries of interest, and in the global sample, using the parameter estimates from Tables 3-5, and 10,000 associated bootstrapped values of these estimates. For the parameter restrictions (a)-(c), we calculate the share of bootstrapped parameter estimates that violate each assumption. A one-sided test of the null hypotheses that each restriction holds would require 95 percent of the bootstrapped estimates to reject it. These results are reported in Panel A of Table 6.\footnote{Chaney’s parameter estimates are more consistent with the theory, and he does not report all of the diagnostics that we report here. In order to produce statistics that allow a comparison, we use his reported point estimates and their standard errors in a bootstrap exercise to generate empirical distributions of $\lambda$ and $\mu$. We use these distributions to generate proxy values of the share of random draws that violate parameter restrictions (a)-(c) in Chaney’s estimates in the conventional data on French firm-level exports that he studies, and report these alongside our estimates from the PayPal data.}

For six of the eight countries, at least one of the parametric conditions is rejected. In the cases of Germany, Canada, Australia, Japan and France, the $\lambda$ parameter is too small in all 10,000 bootstrapped estimates. In the case of India, the $\lambda$ parameter is large enough to meet condition (a), but too large to satisfy condition (c). These six countries do not qualify for formal testing of Chaney’s Proposition 1, though it is nonetheless useful to document their departures from the theory.

The key parameter of interest in this study is $\mu$. The point estimates of $\mu$ reported in Table 4 are mostly positive, as the theory requires. These estimates also come with standard errors, and the second row of Panel A of Table 6 shows that relatively few of the bootstrap estimates violate the condition $\mu > 0$. The only country where this restriction is frequently violated is India, which has a point estimate of $\mu = -0.01$ in Table 4.

The results in Panel A of Table 6 show that the parametric restrictions of Chaney’s theory cannot be formally rejected in the cases of China, the United States, and in the global estimates. While the point estimates for China and the United States clearly satisfy Chaney’s conditions, parameter uncertainty still generates a sizable share of failures. In the U.S. data, 55 percent of the bootstrapped $\lambda$ parameters take values less than one. Both China and the U.S. have point estimates of $\mu$ that are much lower than Chaney’s. The lower values of $\mu$, when combined with parameter uncertainty, generate a somewhat higher share of observations that violate parameter restriction (c) in data for China and for the U.S. than Chaney observes. The estimate of $\lambda = 0.97$ in the global merchant size distribution means that a large proportion of the bootstraps violate condition (a). But since 10 percent of the observations satisfy the constraint we do not treat this as a rejection of the theory’s parametric restriction, and move to a formal evaluation of Chaney’s hypothesis about the distance elasticity in the global data.
Panel B of Table 6 reports statistics that are used to test the hypothesis that the formula in equation (8) predicts the estimated values of $\zeta$ reported in Table 5. We calculate statistics for all eight countries, and for the global sample, but only perform formal testing on the results from China, the U.S. and the globe. The first row of Panel B applies Chaney’s non-linear formula for $\zeta$ using the point estimates of $\lambda$ and $\mu$ from Tables 3 and 4. The second row of panel B reports a 95 percent confidence interval for this predicted distance elasticity, which is calculated with the bootstrapped values of $\lambda$ and $\mu$. In cases where the distribution of $\mu$ estimates centers around zero, the 95 percent confidence intervals for $\zeta$ become enormous. This is most evident in the cases of Canada, India, Australia and France. Even in the cases where the theory’s parametric assumptions are satisfied (China, the U.S. and the global sample), the confidence intervals are quite wide, a result of the statistical uncertainty about the $\lambda$ and $\mu$ parameters and the non-linearity of equation (8). Row 3 of Panel B reports the estimated distance elasticity of exports in the gravity regression (these results reproduce estimates from Table 5). Row 4 reports a $p$-value of the Wald test that the estimate in Row 3 is equivalent to that in Row 1.

Using the formal $\chi^2$ test that Chaney proposes, we are able to formally reject the hypothesis that equation (8) predicts the distance elasticity reported in Table 5 for China and for the globe. In the case of China, the positive distance elasticity of bilateral payment value is clearly unusual, and probably due to competition from other payment platforms in Asian markets. In the case of estimates for the globe as a whole, a point estimate of $\lambda = 0.97$ does not strictly qualify for Chaney’s theory, even if 10 percent of the bootstrap estimates do, so a formal rejection of the theory’s prediction for $\zeta$ is perhaps not surprising.

Moving on to the U.S. estimates we find a curious result. The point estimates of $\lambda=1.00$ and $\mu=0.01$ satisfy the theory’s preconditions, but just barely so. The estimated distance elasticity from the gravity regression is -0.4, which is much smaller than the -1 value that Chaney’s theory predicts. But the structural parameters are so near the knife-edge that equation (8) produces a mean distance elasticity prediction of -0.48, not -1. The proximity of this value to -0.4 means that we are unable to reject the theory in the case of the U.S. data, even though the point estimate is much smaller in magnitude than the motivating value in Chaney’s theory, a distance elasticity of -1. The confidence interval for the predicted distance elasticity is once again quite wide, substantially reducing the statistical power of the test. Any estimate of $\zeta \in [-8.96, 8.26]$ would be consistent with an acceptance of the null hypothesis in the U.S. data.

The overarching lesson we draw from this exercise is that the lower values of $\mu$ observed in the PayPal data give Chaney’s theory considerably less bite in these data. On one hand, the theory

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53 Nonetheless, the estimated $\lambda$ and $\mu$ parameters for Chinese data are consistent with Chaney’s theory, and we might therefore have expected Chaney’s prediction for $\zeta$ to hold in China’s case.
presupposes substantial heterogeneity in firm sizes, and the PayPal data reveals substantial heterogeneity in all eight countries we study (even though Zipf’s law does not always hold). On the other hand, the theory also supposes that relatively larger merchants will sell over much longer distances than relatively smaller merchants. This hypothesis cannot be formally rejected in the PayPal data, but the much lower values of $\mu$ in the PayPal sample indicate a substantially weaker relationship between exporter scale and scope. When this relationship is especially weak and/or imprecisely estimated, the theory’s prediction for the distance elasticity lacks meaningful empirical content. The confidence intervals we calculate would allow an enormous range of estimated distance elasticities to be consistent with the theory.

Section V. Effects of account age on PayPal exports

Our data also include information on the date on which each merchant first established a PayPal account. This information can offer further perspective on whether or not consistent patterns of growth of export sales on the platform are responsible for variation in the scale and geographic scope observed in the 2016 cross-section of merchants. To investigate this possibility, we estimate merchant-level regressions that relate the age of merchants’ accounts to variables representing the scale of merchants’ PayPal exports and the average distances of those exports. Although we lack data on the age of the merchants themselves, we are able to study the question of whether the age of a merchant’s PayPal account affects the scale and scope of their export sales on the platform.

So far, we have followed Chaney in using size bins as the unit of observation in regressions that study the size distribution of merchants’ sales. At this stage we switch to estimating regressions that exploit merchant-level data. Merchant-level regressions have more statistical power, and are more easily interpreted. We calculate, for each payment-receiving merchant $r$, its total sales and the value-weighted average distance of its export sales (in the 24-day sample) and regress these statistics on the age of the merchant’s PayPal account.

Specifically, for each of the eight countries of interest, we estimate

$$\ln(V_i^r) = \alpha_i + \beta_i \ (Age_i^r) + u_i^r,$$  \hspace{1cm} (9)

where $V_i^r$ is total value of payments received by merchant $r$ (which is located in iso-region $i$) and $Age_i^r$ is age of the merchant’s PayPal account (in discrete years). Next, we calculate a weighted average distance of export sales: $\bar{D}_i^r = \frac{\sum_j V_{ij}^r dist_{ij}}{\Sigma e V_{ij}^r}$, and estimate the relationship between this variable and account age:

$$\ln(\bar{D}_i^r) = \alpha_i + \beta_i \ (Age_i^r) + \varepsilon_{if}.$$ \hspace{1cm} (10)

We estimate individual regressions for each of the eight countries chosen. We also estimate versions of equations (9) and (10) that pool over all the countries in the global sample, using origin-country fixed
effects to control for idiosyncrasies in the local history of PayPal activity as well as the geographic position of iso2 regions on the globe.

Results

Table 7 reports the estimates of merchants’ log total international sales on account age, as in equation (9). In the country-level regressions we estimate coefficients ranging from 0.07 (China) to -0.08 (France and Germany), with no consistent sign pattern across countries. Estimates of $R^2$ are also quite small, indicating that account age has almost no predictive value for the value of PayPal merchants’ international sales. In the pooled regression with country fixed effects, we find that the age of a merchant’s account has a small (but statistically significant) negative effect on its international PayPal sales. The coefficient estimate suggests that an additional year on the platform is associated with a 1 percent reduction in a merchant’s total export sales.

In the context of the standard explanation for Zipf’s law (e.g., Gabaix, 1999) the indeterminate results mean either that a) the distribution of merchants’ sales activity in their initial year on the platform is very heterogeneous, or b) the stochastic process for sales growth has a very high variance. Both of these are likely. In the specific context of PayPal it is useful to understand that many of the earliest users of PayPal were eBay sellers – often hobbyists and collectors – and one might not expect the sales of eBay sellers to grow at the same rates as other retailers. The historical link to eBay is one possible explanation for the negative regression coefficient.54 One must also keep in mind that PayPal is just one of many available transaction technologies - including other innovative payment technologies, credit cards, wire transfers, etc. - while our data only track transactions that take place on the PayPal platform itself. Large (and perhaps already old) firms may have entered the platform at relatively late dates, and entered at significant scale. Moreover, the growth rate of merchants’ sales is likely to be volatile because it includes variation over time in consumers’ preferred choice of payment technology. The results in Table 7 do make it clear that age of PayPal merchants’ accounts plays virtually no role at all in explaining the total value of their sales on the platform.

A related thesis in the Chaney model – and in other models of firm export growth (e.g., Morales, et al. 2019) – is that firms’ export sales grow, at least in part, through growth over time in the average distance of export activity. Table 8 reports results from regressions of the log average distance of merchants’ export sales on the platform against the age of their accounts.55 Once again the $R^2$ estimates

54 Note, though, that the lower bound of $10,000 of export receipts within the 24-day sample period is likely to screen out large numbers of small eBay sellers.
55 We also estimated regressions in which we replaced $D_\theta$ with the square of the value weighted average distance. This variable is most relevant for Chaney’s theory, but we report estimates for $D_\theta$ because they are easier to
are very low, indicating that account age plays an ancillary role in explaining average export distance on the platform. With the exceptions of India and Canada, the hypothesis that account age should be positively linked to the average distance of export sales is confirmed. However, the estimated effects of account age on average distance are extremely small. The strongest estimated effect is for Germany, where each additional year of account age leads to a six percent increase in the average distance of a merchant’s exports. In the pooled global regression, we estimate that the cross-country average effect of an additional year of account age raises average export distance by a mere one percent.

These regressions offer further indications that neither the distribution of merchant sizes nor the average distance over which the merchants export are driven by the kinds of growth processes that typically rationalize the empirical findings of power laws commonly observed in the data. The export profile of merchants that joined PayPal recently are nearly identical, on average, to the profiles of merchants from the same country that joined the platform much earlier. The PayPal platform is not a closed environment, so growth on the platform may not operate strictly as it would if we saw merchants’ sales across all forms of payment. This explanation for the insignificance of account age on export sales on PayPal is plausible, and even likely, but our results generate an empirical puzzle: Zipf’s law emerges (in the U.S. and Chinese data, at least), but does not appear to do so through the growth mechanisms thought to explain Zipf’s law in other contexts.

Section VI. Conclusion
Cross-border electronic commerce is growing rapidly, and requires further study. A small literature studies both domestic and international trade on electronic marketplaces, such as eBay or Alibaba. In this paper we study the geography of international payments made with a specific electronic payment mechanism, PayPal. PayPal’s role in international e-commerce is different than that of electronic marketplaces, whose primary role is to facilitate the matching of buyers and sellers. PayPal is a global financial intermediary that provides users with payment capabilities in international transactions. PayPal also represents a much broader swathe of online transactions, including, for example, payments for digital goods and services. Despite this difference in economic function between e-marketplaces and online payment solutions, PayPal’s data also reveal a lower distance elasticity of payment value than is observed in conventional trade data. Our findings suggest that a lower distance elasticity may be a general feature of e-commerce, rather than a result that is particular to online marketplaces.

A distinguishing feature of the PayPal data is that the international transactions facilitated by PayPal are much smaller, on average, than is common in conventional international trade flows. The
larger transactions in conventional international trade often require specialized trade finance, which may be provided more readily or more cheaply to firms that are large or trading frequently and in bulk. We conjecture that small firms/infrequent traders are at a smaller disadvantage in distant markets when PayPal is the payment mechanism. A recent theory of gravity-based trade, Chaney (2018), offers a framework for evaluating this intuition.

For our purposes, the key parameter of Chaney’s theory is \( \mu \), which defines the relationship between the value of firms’ total international sales and the average squared distance of these sales. In contrast to what Chaney observes in conventional international trade data, we find that this relationship is weak to non-existent in data on merchants’ international PayPal sales. We attribute the low value of this parameter in our data to the relative lack of geographic constraints on merchants’ initial export sales when they sell over the internet. Put differently, it is likely that PayPal and other fintech mechanisms that facilitate payments over the internet allow firms that are small and/or inexperienced in international trade to more easily penetrate distant international markets. While our data cannot show that PayPal reduces the absolute costs of international trade, the data patterns are consistent with the view that the platform reduces (and nearly eliminates) the relative penalty that distance imposes on firms that are small and/or relatively inactive in international sales. This is consistent with the idea that, PayPal is relatively more useful to small/infrequent traders, because these firms benefit disproportionately from PayPal’s reduction of the costs of receiving international payments.

While the detailed documentation of the value and number of PayPal firms’ sales in individual foreign markets offers important new insights into e-commerce, there are nonetheless some caveats to consider. The main issue is that we only see transactions that occur on the PayPal platform. Ideally, we would also see activity undertaken with other payment mechanisms. Our insights are tied to the size of firms, but lacking evidence on off-platform sales, we can only make statements about the relative sizes of firms’ receipts on the PayPal platform itself. Data on non-PayPal transactions would allow us to better understand the conditions that lead economic agents to use the platform, and whether an analysis that uses PayPal data alone suffers from a selection bias that arises from those decisions. Most importantly, we lack data from competing platforms, so our inferences are plausibly affected by the specific geography of PayPal’s userbase. In particular, it is highly plausible that our results for Chinese firms are affected by the predominance of AliBaba in Chinese and other proximate markets.

We view our paper as a novel contribution to the literature on e-commerce. The focus of the literature to date has been on the role of electronic marketplace in reducing search and matching frictions. Our contribution is to focus on the distributional effects of PayPal on firms of different sizes. A wide body of evidence from the international trade literature suggests that the disadvantages that small firms suffer in international trade increase with geographic distance. The evidence presented in this paper
suggests that distance does not pose a significant relative penalty on firms with relatively smaller values of PayPal exports. This fact is informative about the function that PayPal plays in international trade.

References


Table 1. Descriptive Statistics

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<th>Std. Dev.</th>
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Table notes: Summary statistics for the 24-day data sample from 2016, at various levels of aggregation. Panel A reports results for aggregates at the iso2 region pair level. These data aggregate over merchants of all sizes and include within-region payment activity. Panel B reports data at the firm by destination region level, the most detailed data available. These data exclude intra-regional transactions and merchants with less than $10,000 in international PayPal receipts (sales). Panel C reports statistics for an aggregation of data to the level of individual merchant. These data also exclude intra-regional transactions and merchants with less than $10,000 in international PayPal receipts within the 24-day sample period.
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<td>(0.06)</td>
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<td>Home</td>
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<td>12,872</td>
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<td>R²</td>
<td>1.00</td>
<td>1.00</td>
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</table>

Table notes: PPML gravity regressions of the value of sales, transactions and firms on logged distance and a home dummy variable. All regressions contain comprehensive vectors of origin region and destination region fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. These results exclude bilateral flows with zero values for payments. A PPML regression that includes zero values returns the same coefficients with only slightly larger standard errors.
Table 3. Evaluating Zipf's Law

<table>
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<tr>
<th>Payment receiving country</th>
<th>China</th>
<th>United States</th>
<th>Germany</th>
<th>Canada</th>
<th>India</th>
<th>Australia</th>
<th>Japan</th>
<th>France</th>
<th>Global sample</th>
<th>Chaney (2018) estimates</th>
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<tr>
<td>Mean firm size (-(\lambda))</td>
<td>-1.02***</td>
<td>-1.00***</td>
<td>-0.86***</td>
<td>-0.87***</td>
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<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.02)</td>
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<td>45</td>
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<td>44</td>
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<td>41</td>
<td>44</td>
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<tr>
<td>R²</td>
<td>1.00</td>
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<td>0.99</td>
<td>1.00</td>
<td>0.98</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
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</tbody>
</table>

Table notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The regressions estimate the parameter of a Pareto distribution for firms’ international receipts (exports). Regressions follow Chaney (2018) and equation (4) in the text. Columns (1) – (8) are for individual countries; column (9) is for the global distribution of firm-level receipts. Column (10) is for comparison purposes and reports results from comprehensive French data on firm-level exports. Data used in the analysis are from all firms that receive $10,000 in PayPal payments within the data sample. Firms are grouped into 50 bins of equal sizes (in logs). In the country-level regressions some bins are not populated due to the relatively low density of merchants with high values of PayPal receipts at the country-level.
Table 4. Estimating the relationship between total merchant sales and average payment distance

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<th>(4)</th>
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<td></td>
<td></td>
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<tr>
<td>Mean firm size (\mu)</td>
<td>0.03***</td>
<td>0.01***</td>
<td>0.08***</td>
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<td>44</td>
<td>41</td>
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<tr>
<td>(R^2)</td>
<td>0.88</td>
<td>0.88</td>
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<td>0.71</td>
<td>0.04</td>
<td>0.73</td>
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Table notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The regressions estimate the structural relationship between the scale of a PayPal merchant’s receipts and the (squared) distance of its international transactions. Regressions follow Chaney (2018) and equation (6) in the text. Columns (1) – (8) are for individual countries; column (9) reports results for a global regression that pools country-level results and employs export-country fixed effects. Data used in the analysis are from all merchants that receiving $10,000 or more in PayPal payments within the data sample. Column (10) is for comparison purposes and reports results from comprehensive French data on firm-level exports. Merchants are grouped into 50 bins of equal sizes (in logs). In the country-level regressions some bins are not populated due to the relatively low density (at the country-level) of merchants with extremely high values of PayPal receipts.
Table 5. Country-level gravity regressions

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<tr>
<td>ln(distance_{ij})</td>
<td>0.26***</td>
<td>-0.40***</td>
<td>-0.84***</td>
<td>-0.16</td>
<td>-0.24</td>
<td>-0.95***</td>
<td>-1.22***</td>
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<td>-0.70***</td>
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<td>(0.25)</td>
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<td>(0.215)</td>
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<tr>
<td>ln(imports_{j})</td>
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<td>0.94***</td>
<td>1.08***</td>
<td>0.98***</td>
<td>0.95***</td>
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<td>1.05***</td>
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<td>0.93</td>
<td>0.81</td>
<td>0.69</td>
<td>0.84</td>
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Table notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The table reports gravity model estimates for each country’s international receipts on the platform (i.e. exports) following equation (7) in the text. Columns (1) – (8) are for individual countries; column (9) is a pooled regression with export-specific fixed effects using a global sample. Column (10) is for comparison purposes and reports the results from Chaney (2018), which uses data on exports of French manufacturing firms with more than 1 million French Francs (approximately US$200,000) of export value. PayPal data used in columns (1)-(9) are from all merchants receiving at least $10,000 in PayPal payments within the data sample.
Table 6. Formal tests of parameter restrictions and implications

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<td>France</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Globe</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Chaney (2018)</td>
</tr>
<tr>
<td>Panel A. Share of bootstrapped estimates that contradict parametric assumptions of the theory</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda &lt; 1$</td>
<td>.10</td>
<td>.55</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>.90</td>
<td>.42a</td>
</tr>
<tr>
<td>$\mu &lt; 0$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.03</td>
<td>.92</td>
<td>.02</td>
<td>0</td>
<td>.15</td>
<td>0.02</td>
<td>0a</td>
</tr>
<tr>
<td>$\lambda \geq 1 + \mu$</td>
<td>.22</td>
<td>.27</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Panel B. Test of null hypothesis $\zeta_{long} = 1 + 2(\lambda - 1)/\mu$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\zeta = 1 + 2(\lambda - 1)/\mu$</td>
<td>2.30</td>
<td>0.48</td>
<td>-2.36</td>
<td>-32.86</td>
<td>-57.01</td>
<td>-58.60</td>
<td>-5.36</td>
<td>-69.55</td>
<td>-1.36</td>
<td>1.086</td>
</tr>
<tr>
<td>Estimated $\zeta_{long}$</td>
<td>-0.261</td>
<td>0.402</td>
<td>0.843</td>
<td>0.156</td>
<td>0.239</td>
<td>0.950</td>
<td>1.221</td>
<td>0.830</td>
<td>0.699</td>
<td>1.090</td>
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<tr>
<td>p-value of $\chi^2$ test</td>
<td>.002**</td>
<td>.119</td>
<td>ng</td>
<td>ng</td>
<td>ng</td>
<td>ng</td>
<td>ng</td>
<td>ng</td>
<td>ng</td>
<td>0.00***</td>
</tr>
</tbody>
</table>

Table notes: Panel A uses the results of 10,000 bootstrapped estimates of $\lambda$ and $\mu$ to report the share of observations that contradict the three parameter restrictions that underpin the gravity theory of Chaney’s (2018). Panel B reports the predicted distance elasticity, a 95 percent confidence interval from the bootstraps, the estimated distance elasticity for distances > 2000 km ($\zeta_{long}$), and the p-value of the $\chi^2$ test that $\zeta_{long} = \zeta$. Columns (1) – (8) report results for the eight columns of interest. Column (9) for global estimates explained in Tables 2 and 3. Column 10 reports results from Chaney (2018) for comparison purposes (a indicates author’s simulation from estimates reported in Chaney (2018)). ng in panel B indicates that the parameter estimates in Panel A do not qualify for hypothesis testing (every one of the 10,000 bootstrap estimates fails to satisfy at least one of the parametric restrictions.) ***p <0.01, **p<0.05.
Table 7: Effects of account age on the log size of merchant’s international PayPal sales

<table>
<thead>
<tr>
<th></th>
<th>(1) China</th>
<th>(2) United States</th>
<th>(3) Germany</th>
<th>(4) Canada</th>
<th>(5) India</th>
<th>(6) Australia</th>
<th>(7) Japan</th>
<th>(8) France</th>
<th>(9) Global (pooled)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Account age</td>
<td>0.07***</td>
<td>-0.01***</td>
<td>-0.08***</td>
<td>0.01*</td>
<td>0.05***</td>
<td>0.01</td>
<td>0.02***</td>
<td>-0.08***</td>
<td>-0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Observations</td>
<td>23,013</td>
<td>22,250</td>
<td>5,119</td>
<td>3,282</td>
<td>3,215</td>
<td>2,888</td>
<td>1,542</td>
<td>1,432</td>
<td>86,030</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.02</td>
<td>0.00</td>
<td>0.03</td>
<td>0.00</td>
<td>0.03</td>
<td>0.00</td>
<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Table notes: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the log of international sales for merchants receiving at least $10,000 in international PayPal sales within the data sample. The independent variable is the number of years since the merchant opened a PayPal account. Positive coefficients indicate that merchants that have spent more years on the platform receive more in international payment value. The regression constant is suppressed. Columns (1)-(8) report results for individual countries. Column (9) reports results for a pooled regression of all countries. The latter regression includes country fixed effects.
Table 8: Effects of account age on the log average distance of merchants’ international PayPal sales

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>China</td>
<td>United States</td>
<td>Germany</td>
<td>Canada</td>
<td>India</td>
<td>Australia</td>
<td>Japan</td>
<td>France</td>
<td>Global (pooled)</td>
</tr>
<tr>
<td>Account age</td>
<td>0.00***</td>
<td>0.01***</td>
<td>0.06***</td>
<td>-0.00</td>
<td>-0.00***</td>
<td>0.01***</td>
<td>0.02***</td>
<td>0.05***</td>
<td>0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Observations</td>
<td>23,013</td>
<td>22,250</td>
<td>5,119</td>
<td>3,282</td>
<td>3,215</td>
<td>2,888</td>
<td>1,542</td>
<td>1,432</td>
<td>86,030</td>
</tr>
<tr>
<td>R²</td>
<td>0.00</td>
<td>0.01</td>
<td>0.06</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.04</td>
<td>0.05</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the log of the average distance of international sales for firms with more than $10,000 in international PayPal sales within the data sample. The independent variable is the number of years since the firm opened a PayPal account. Positive coefficients indicate that firms with older accounts sell over longer distances. The regression constant is suppressed. Columns (1)-(8) report results for individual countries. Column (9) reports results for a pooled regression including all countries. The latter regression includes country fixed effects.