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Borders and Big Macs*

Anthony Landry
Federal Reserve Bank of Dallas

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Abstract

I measure the extent of international market segmentation using local, national, and international Big Mac prices. I show that the bulk of time-series price volatility observed across the United States arises between neighboring locations. Using these data, I provide new estimates of border frictions for 14 countries. I find that borders generally introduce only small price wedges, far smaller than those observed across neighboring locations. When expressing these wedges in terms of distance equivalents, I find that border widths are small in relation to price variations observed across the United States. This suggests that international markets are well integrated.

JEL codes: F4

* Anthony Landry, Federal Reserve Bank of Dallas, 2200 N. Pearl Street, Dallas, TX 75201. 214-922-5831. Anthony.Landry@dal.frb.org. I benefited from the comments of Marianne Baxter, Mario Crucini, Mick Devereux, Charles Engel, Karen Lewis, Ananth Ramanarayanan and Mark Wynne.

1 Introduction

Economists believe that border frictions are large. In a seminal paper, Charles Engel and John Rogers (1996) estimate border frictions on price dispersion across U.S. and Canadian cities. After controlling for distance and other factors, they concluded that the economic impact of crossing the border between the United States and Canada is equivalent to shipping a good 75,000 miles. Numerous subsequent studies estimate even more impressive border frictions. For example, David Parsley and Shang-Jin Wei (2001) find that border frictions between the United States and Canada are equivalent to shipping a good 101 million miles, and the border between the United States and Japan is equivalent to shipping a good 43,000 trillion miles. Given these enormous border frictions, it seems odd that global trade keeps rising.

In this paper, I measure border frictions using local, national, and international Big Mac prices. I show that the bulk of time-series price volatility observed across the United States arises between New York City neighboring locations. Using these data, I provide new estimates of border frictions for 14 countries. I find that borders generally introduce only small price wedges, far smaller than those observed across New York City locations. When expressing these wedges in terms of distance equivalents, I find that border widths are small—and often nonexistent—in relation to price volatility observed across the United States. This suggests that international markets are well integrated.

Over the years, the iconic Big Mac index has been seen as being representative of the hamburger's international prices.[1] The Big Mac is attractive because it is sold all over the world by one single retailer, McDonald's. Another attractive feature of the Big Mac is its uniform composition. With a few exceptions, the ingredients of the Big Mac are the same everywhere. As Vincent said in the classic movie *Pulp Fiction:* "A Big Mac's a Big Mac."

I use 2001-2011 Big Mac prices from *The Economist* newspaper. The McDonald's locations surveyed include 14 international cities and six U.S. cities, including three New York City boroughs. Unlike other countries, the U.S. price published by *The Economist* newspaper is an average of four city prices:

[1] A large literature uses Big Mac prices, including Click (1996), Cumby (1997), Ong (1997), Pakko and Pollard (1996, 2003) and other papers by Parsley and Wei (2007, 2008).

Atlanta, Chicago, New York City, and San Francisco. In turn, the New York City price is an average of three boroughs: the Bronx, Manhattan, and Queens. While the U.S. price is published, I had to ask the newspaper for the national and local breakdowns.

I show that *The Economist* newspaper data are representative by conducting my own survey of Big Mac prices across forty locations in New York City. The survey reveals a large price disparities across neighboring locations. For example, the standard deviation in Manhattan is \$0.20 over an average distance of 2.6 miles from Penn Station. Large price disparities observed in the cross-section should not be a surprise for anybody. Wages, rents and other non-tradable factors that influence production costs vary significantly across locations. Thus, observing the sale of identical goods at different prices in different countries does not tell us much about border frictions because prices vary substantially across locations of the same neighborhood.

A better gauge of border frictions is in the time-series volatility of the real exchange rate. If frictions are small, shocks to the economy should influence Big Mac prices uniformly across local, national, and international locations: Big Mac prices should move in tandem and the real exchange rate should remain constant over time. Previous studies have shown that this is not the case in international data. Movements in the prices of similar goods across borders account for most of real exchange volatility. This time-series pattern of real exchange rate volatility also holds with Big Mac prices: Big Mac real exchange rates are far more volatile between countries than they are across the United States. Big Mac prices also show us, however, that the bulk of the time-series volatility observed across the United States arises within a city. For example, I find that 75 percent of the time-series volatility observed between Manhattan and other United States cities arises between Manhattan and other New York City locations. This is surprising because neighboring locations should respond to similar economic fluctuations.

I look at border frictions implied by Big Mac prices in light of the distribution of prices observed in the United States. I use a regression similar to Engel and Rogers in which I control not only for distance and border effects, but also for heterogeneity within and across U.S. cities. I find that distance is significant in explaining price volatility. Borders, however, are generally not. They introduce a median price wedge of only 1.1 percent. This is far smaller than the time-series volatility observed across New York City locations. When expressing these wedges in terms of distance equivalents, I find that border widths are small—and often nonexistent—in relation to price volatility observed across the United States. For example, the width of the Canadian border is 2 miles and that of Japan is 5 miles. These are much smaller than the estimates reported in Engel and Rogers, and Parsley and Wei.[2]

Recently, other researchers have explored border frictions with micro-data. Using barcode data on prices across the U.S. and Canada, Christian Broda and David Weinstein (2008) find small border frictions. Their estimate of the border is 3 miles. Their data includes perishable products and other consumer non-durables sold by different retailers. Using different data and a different approach, Gita Gopinath et al. (2011) find that the border matters. Their data include retail prices and wholesale costs from a grocery chain operating in the United States and Canada. Here, I compare prices from a single multinational offering a service in 119 countries—of which 15 are in my sample.

In a related paper, Yuriy Gorodnichenko and Linda Tesar (2009) critique the methodology employed by Engel and Rogers, Parsley and Wei, and Broda and Weinstein. They argue that this methodology is not valid because countries are likely to have different price distributions. Since border widths are measured by comparing border coefficients with the within-country price distribution, different within-country price distributions would generate different border widths. In this paper, I have one price for each country outside the United States. Therefore, I can only report border frictions in light of the distributions of prices prevailing in the United States. The takeaway is that border frictions are small, often far smaller than those arising between U.S. neighboring locations.

The paper proceeds as follows. In Section 2, I describe the Big Mac data and show the large price volatility observed in the cross-section and time-series data for local, national, and international locations. In Section 3, I look at the size of border frictions implied by international Big Mac data in light of

[2]Engle and Rogers (2001) found that the distance between cities and the border also have positive and significant effects on real exchange rate volatility using aggregate city-level consumer-price data for European cities.

the distributions of prices prevailing in the United States. I use a regression relating distance and borders on real exchange rate volatility in the spirit of Engel and Rogers. Then, I confirm my results using alternative regression specifications and an alternative dataset of fast food restaurant prices. Section 4 concludes.

2 Price Volatility across Locations

The Economist newspaper has been publishing a Big Mac Index comparing the hamburger prices across countries since 1986. Over the years, this index has been seen as representative of Big Mac prices prevailing around the world. In this paper, I use annual prices from *The Economist* newspaper Big Mac Index from 2001 to 2011. The sample includes locations in 15 countries, including the U.S.[3] The price survey usually takes place during the summer and prices are collected from the same locations across years. I use annual survey dates spot exchange rates to translate local currency prices into U.S. dollars.

Unlike other countries, the U.S. price published by *The Economist* newspaper is an average of four city prices: Atlanta, Chicago, New York City, and San Francisco. In turn, the New York City price is an average of three boroughs: the Bronx, Manhattan, and Queens. While the U.S. price is published, I had to ask the newspaper for the national and local breakdowns. The entire sample allows me to study Big Mac prices across local, national, and international locations.

Table 1 shows U.S. dollar Big Mac prices. The table shows large price disparities at the local, national, and international level. In 2011, the cheapest Big Mac was $1.94 in Hong Kong, while the most expensive was $8.06 in Switzerland. In the U.S., prices range from $3.51 in Atlanta to $4.56 in the Bronx. Large price disparities even exist between New York City locations: A Queens' Big Mac was a bargain at $4.13, just 9 miles away from the Bronx.

[3]The countries (and cities) in my sample are: Australia (Sydney), Brazil (Sao Paulo), Canada (Toronto), China (Beijing), Germany (Berlin), Hong Kong, Japan (Tokyo), Mexico (Mexico City), Russia (Moscow), Thailand (Bangkok), South Korea (Seoul), Switzerland (Zurich), Sweden (Stockholm), and the United Kingdom (London).

To confirm the extent of price dispersion within New York City observed in *The Economist* sample, I complement the data with my own survey of Big Mac prices for 40 McDonald's locations across New York City. The restaurants surveyed represent a wide range of locations including airports and train stations, shopping streets, and service roads, etc. The data were collected during the week of July 17, 2011.[4] Table 2 shows the surveyed location prices and distance from Penn Station. The table confirms that the New York City price disparities reported by *The Economist* newspaper are representative of the various prices observed in New York City. The standard deviation in Manhattan is $0.20 over an average distance of 2.6 miles from Penn Station. This represents 5 percent of the Manhattan price in 2011 ($4.24). The standard deviation over the various New York City suburbs is $0.34 over an average distance of 9.6 miles from Penn Station. This represents 8 percent of the average New York City price in 2011 ($4.31). These price disparities between neighboring locations echo my earlier findings on Big Mac prices in Dallas–see Landry (2008).

The large price disparities observed within and across U.S. cities should not be surprising to anybody. Wages, rents, and other non-tradable factors that influence production costs vary significantly across locations. Thus, observing the sale of identical goods at different prices in different countries does not tell us much about border frictions because prices vary substantially across locations of the same city: Price disparities do not necessarily imply border frictions.

A better gauge of market integration is in the time-series volatility of the real exchange rate. The real exchange rate is the relative prices of Big Macs between two locations, in U.S. dollars. If markets are well integrated, shocks to the economy should influence prices uniformly across locations: Big Mac prices should move in tandem, and the real exchange rate should remain constant over time. To test this alternative, I study the behavior of real exchange rate volatility and distance in the rest of this section. I start with an example in which I look at real exchange rate volatility and distance relative to Manhattan; then I generalize my results by looking at all city pairs.

Table 3 shows time-series of Big Mac prices relative to Manhattan, in

[4] For the 2011 edition, *The Economist* surveyed Big Mac prices on July 7, 2011.

log–or the log of the real exchange rate. The last column of Table 3 shows the time-series standard deviations. Consistent with the literature on international prices, real exchange rates between international locations are more volatile than real exchange rates between U.S. locations: The average standard deviation between Manhattan and international locations is 0.19, while that between Manhattan and other U.S. cities in 0.12. The striking result from Table 3 is that the bulk of the real exchange rate volatility observed between Manhattan and other U.S. cities arises between Manhattan and other New York City locations–locations within a few miles of each other. This is surprising because neighboring locations should respond to similar economic fluctuations.[5]

Table 4 shows statistics across New York City, U.S., and international locations: New York City locations include all New York City pairs, U.S. locations include all U.S. pairs (excluding New York City pairs), and international locations include all international pairs. The first column of Table 4 shows standard deviations averages of the real exchange rates. For example, the average standard deviation within U.S. locations is 0.094, while that across U.S. and international locations is 0.177. Therefore, moving from within U.S. locations to across U.S. and international locations roughly doubles real exchange rate volatility.

The last column of Table 4 shows distance averages. For example, the average standard deviation between New York City locations is 0.086 over an average distance of 9 miles, while the average standard deviation between U.S. locations is 0.094 over an average distance of 1394 miles. This confirms that the bulk of the real exchange rate volatility observed across U.S. locations arises between neighboring New York City locations.

The international finance literature emphasizes distance as a robust determinant of trade friction and hence price dispersion (for example, see Marianne Baxter and Michael Kouparitsas (2005)). The last row of Table 4 shows the correlation between standard deviation averages and distance averages. The correlation is computed over all New York City, U.S., and international locations. The positive correlation (0.68) suggests that distance can explain real

[5] Note that the highest real exchange rate volatility between U.S. cities are between the neighboring locations of Manhattan and the Bronx.

exchange rate volatility.

Because prices in the international finance literature are usually aggregates rather than transaction prices, Engel and Rogers use the standard deviations of changes in the real exchange rate. Taking differences in the real exchange rate implies that one is testing relative rather than absolute purchasing power parity. It also helps to reduce the persistence of the real exchange rate and may be appropriate for a few of my city pairs where the price ratios appear to drift. The second column of Table 4 shows the standard deviations in the log difference of the real exchange rate. This column shows that the log difference generally display the same patterns of real exchange rate volatility over distance than the level of the real exchange rate.

3 Distance and Border Frictions

In this section, I look at the size of border frictions implied by international Big Mac data in light of the distribution of prices prevailing in the United States. I use a regression relating distance and borders on real exchange rate volatility in the spirit of Engel and Rogers. Then, I confirm my results using alternative specifications and an alternative dataset of fast food restaurant prices.

3.1 The Regressions

I explore border frictions with the following regression:

$$\sigma\left(q_{j,k}\right) = \beta d_{j,k} + \sum_{i=1}^{I} \gamma_i B_i + \sum_{n=1}^{N} \delta_n C_n + \varepsilon_{jk}, \tag{1}$$

where $\sigma\left(q_{j,k}\right)$ is the standard deviation of the time-series real exchange rate between location j and k, and d is the log of the greater-circle distance (in miles) between location j and k. The great-circle distance is computed by using the latitude and longitude of each location. The log distance is consistent with the concave relationship between relative price volatility and distance observed in my sample of locations. Because two Big Macs sold in the same location should have the same price, I do not include a constant in the regression. I explore the consequences of adding a constant below, together with other alternative specifications and robustness checks. The regression error is denoted by ε_{jk}.

I include border dummies B_i for locations outside the U.S. These 14 dummies are equal to 1 if the locations are outside the United States and 0 otherwise. This set of dummies ensures that the border relationship holds not only between U.S. and international locations, but also across international locations. The interpretation of these coefficients is the difference between the average standard deviation of real exchange rate for location pairs that lie in different countries less the average for location pairs that lie in the United States, taking into account the effect of distance. The border coefficients represent a measure of frictions associated with crossing the border. Although these coefficients are unitless, I interpret them in terms of mileage equivalent for the purpose of comparability with the literature. From this perspective, border widths represent the additional distance one would have to travel relative to the distribution of prices across locations existing in the United States over the period 2001 to 2011.

I also include city dummies C_n for U.S. locations outside New York City. These three dummies (Atlanta, Chicago and San Francisco) are equal to 1 if the locations are outside New York City and 0 otherwise. This set of dummies controls for factors unrelated to the distance between two U.S. cities, such as different schemes of sales and corporate taxation, different sets of competitors, different promotions, etc. The city coefficients represent the difference between the average standard deviation of real exchange rate for location pairs that lie in different U.S. cities less the average for location pairs that lie in New York City, taking into accounts the effect of distance.

The first two columns of Table 5 show the coefficients and standard deviations results from regression (1). I find strong evidence that distance is helpful in explaining real exchange rate volatility. The coefficient on the log of distance is positive and significant. However, four border coefficients are negative and eight border coefficients are not significantly different than zero. This implies that there are no significant frictions associated with over half of the borders in the sample. Note that the coefficient on Brazil is extremely high relative to other coefficients, probably because of the drift we observe in the Brazilian price. Below, I re-estimate (1) using the standard deviations in the log difference of the real exchange rate to address this issue. Looking at the entire set of border coefficients, borders introduce a median price wedge of only 1.1 percent and an average price wedge of 2.5 percent between countries. These numbers are smaller than the time-series standard deviations of prices observed in New York City.

To provide a sense of the width of the border, Engel and Rogers use the mileage equivalent of the border coefficient calculated as $\exp(\widehat{B}_i/\widehat{\beta})$. The border widths are displayed in the third column of Table 5. All border widths are only a few miles, with the exception of Brazil. For example, the width of the Canadian border is 2 miles. By contrast, the point estimate in Engle and Rogers was 75,000 miles–and $8.28\text{x}10^{22}$ miles for the food away from home category, the Big Mac category.

Because coefficient estimates are unaffected by change in the units of measurement, Parsley and Wei suggest an alternative measure to compute border widths. They scale Engel and Rogers estimates by the average distance between countries. Their measure is calculated as $\overline{d} \times \exp(\widehat{B}_i/\widehat{\beta} - 1)$, where $\overline{d}$ is the average distance between countries from Table 4. The new border widths are displayed in the fourth column of Table 5. The median border width is 2,883 miles. The width of the Canadian border is 3,270 miles and that of Japan is 9,934. By contrast, Parsley and Wei estimate the U.S.-Canada border to be 101 million miles and that of U.S.-Japan to be 43,000 trillion miles.

The last three rows of Table 5 show the city coefficients. The coefficients are negative–although the coefficient on Chicago is not significantly different than zero. This implies that, after taking into account the effect of distance, the difference between the average real exchange rate standard deviations between U.S. cities are smaller than that within New York City. This is consistent with the bulk of the standard deviation in the U.S. time-series real exchange rate arising from neighboring locations.

In the last column of Table 5, I re-estimated (1) using the standard deviations in the log difference of the real exchange rate. The distance and border coefficients tell the same story: Distance helps explain real exchange rate volatility, while borders generally, do not. One border coefficient is negative and four are not significantly different than zero. The border introduces a median wedge of 1.2 percent and an average wedge of 1.8 percent. The coefficient on Brazil is now in line with other coefficients and implies a Brazilian border of 55 miles using Engel and Rogers methodology.

3.2 Alternative Specifications and Robustness Checks

I look at the robustness of my results by providing alternative specifications to (1). The first alternative specification adds a constant α:

$$\sigma\left(q_{j,k}\right) = \alpha + \beta d_{j,k} + \sum_{i=1}^{I} \gamma_i B_i + \sum_{n=1}^{N} \delta_n C_n + \varepsilon_{jk}. \tag{2}$$

This specification implies that price volatility jumps to α for locations adjacent to each other. Although this is not what my theory calls for, it may be the appropriate specification if the data contain common factors between location pairs that are not related to distance. Table 6 shows the results. The constant is positive and significant, but my general conclusion, that border frictions are small, does not change: four border coefficients are negative and seven border coefficients are not significantly different than zero.

The second specification treats all U.S. cities equally, by including a dummy variable for each U.S. location, regardless of whether they belong to New York City or not. This specification implies that each location is unique. Table 7 shows the results. The dummy coefficients on the Bronx and Queens are insignificant in the level regression. This is consistent with treating New York City boroughs as one city.

The third specification uses the average price observed in New York City. This specification implies that neighboring price volatility are unimportant in understanding real exchange rate movements. The volatility to look for arises only at the national level. Table 8 shows the results. The dummy coefficients are all insignificant in the level regression. Therefore, adding neighboring locations adds information to the regression.

Finally, I estimate (1) independently for each international location relative to the United States. This implies running 14 regressions in which each border coefficient is estimated in relation to the U.S. distribution of prices alone–and not in relation to other international locations. Table 9 shows the results. The results are essentially the same: Distance is significant in explaining real exchange rate volatility, while borders are usually not; three border coefficients are negative and four border coefficients are not significantly different than zero. Moreover, I cannot reject the hypothesis that the distance coefficients are the same across regressions, which implies that pulling all locations into one regression is appropriate.[6]

3.3 Big Mac and other Fast Food Prices

I confirm my findings by using another dataset of fast food prices. I use annual data from the category labeled "Fast food snack: hamburger, fries and drink" from the Economist Intelligence Unit Worldwide Survey of Retail Prices from 1995 to 2005. This survey covers the same cities available in my Big Mac prices sample–including New York City but not the breakdown of its boroughs. Although I don't know the name of the outlet surveyed, I know that prices were collected from the same locations over time. I use annual survey dates spot exchange rates to translate local currency prices into U.S. dollars.

Table 10 shows the results based on (1). Once again, I find strong evidence that distance is helpful in explaining real exchange rate volatility. The coefficient on the log of distance is positive and significant. However, five border coefficients are negative and seven border coefficients are not significantly different than zero. This confirms that there are no significant frictions associated with borders. As with Big Mac prices, borders introduce only small price wedges: The median price wedge is 0.8 percent and the average price wedge is 3.3 percent. Using the real exchange rate in log differences (right part of the Table 10) or adding a constant to the regression conveys the same general message.[7]

[6] Adding a constant to all of the above specifications does not change the message of this paper.

[7] I also found similar results using other food away from home categories from the Economist Intelligence Unit Worldwide Survey of Retail Prices such as "One drink at a bar of first-class hotel," "Simple meal for one person," "Two-course meal for two people," and "Three-course dinner for four people".

4 Conclusion

This paper looks at international market segmentation using local, national, and international Big Mac prices. The conclusion from the exercise above is that borders do not introduce significant frictions, over and above the effect of distance. This suggests that international markets are well integrated. Although this conclusion is in sharp contrast with most previous studies, it should not come as a surprise given that the bulk of the time-series volatility in real exchange rate comes from neighboring locations.

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Table 1
Big Mac Prices (in U.S. dollars)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
New York City											
Manhattan											
Bronx											
Queens											
Average						***Unpublished Data***					
						Available from The Economist upon request					
United States											
New York (average)											
Chicago											
San Francisco											
Atlanta											
Average											
International											
United States (average)	2.59	2.49	2.71	2.90	3.06	3.15	3.40	3.57	3.54	3.73	4.07
Australia	1.52	1.61	1.86	2.27	2.50	2.44	2.97	3.30	3.49	3.86	4.95
Brazil	1.64	1.54	1.48	1.70	2.39	2.79	3.60	4.75	4.16	4.92	6.17
Canada	2.13	2.12	2.21	2.32	2.64	3.14	3.70	4.04	3.48	4.00	5.01
China	1.20	1.27	1.20	1.26	1.27	1.31	1.45	1.83	1.83	1.95	2.28
Germany/Euro	2.30	2.38	2.98	3.28	3.58	3.78	4.16	5.28	4.68	4.34	4.94
Hong Kong	1.37	1.44	1.47	1.54	1.53	1.55	1.54	1.58	1.72	1.90	1.94
Japan	2.37	2.02	2.18	2.33	2.34	2.23	2.30	2.60	3.41	3.69	4.09
Mexico	2.36	2.36	2.18	2.08	2.58	2.57	2.69	3.19	2.43	2.50	2.74
Russia	1.21	1.25	1.32	1.45	1.48	1.77	2.02	2.53	2.11	2.33	2.70
Thailand	1.21	1.27	1.38	1.45	1.48	1.56	1.96	1.85	1.89	2.17	2.35
South Korea	2.26	2.38	2.70	2.72	2.49	2.63	3.15	3.18	2.68	2.82	3.51
Switzerland	3.64	3.80	4.60	4.90	5.05	5.23	5.20	6.26	6.06	6.22	8.06
Sweden	2.33	2.52	3.60	3.94	4.17	4.54	4.86	6.29	5.00	6.58	7.64
United Kingdom	2.85	2.89	3.14	3.38	3.44	3.65	4.00	4.54	3.77	3.49	3.89

Source: *The Economist* newspaper

Table 2
New York City Big Mac Prices Surveyed in July 2011

Manhattan Prices

Location	Distance from Penn Station (in miles)	Price
Penn Station	-	$ 4.19
Time Square	0.8	$ 3.99
Downtown	1.1	$ 3.99
Downtown	1.2	$ 4.17
Downtown	1.5	$ 3.99
Houston St.	1.7	$ 3.99
SoHo	1.8	$ 3.89
NoHo	2.1	$ 3.78
East Village	2.5	$ 3.69
Lafayette	2.5	$ 3.99
Manhattan	2.9	$ 3.59
Tribeca	2.9	$ 4.19
Downtown	3.0	$ 4.18
Financial district	3.3	$ 4.19
Financial district	3.5	$ 3.79
Manhattan	3.5	$ 3.97
Lower East Side	3.6	$ 3.69
Upper West Manhattan	3.6	$ 3.69
Uptown	4.1	$ 3.79
Yorkville Area	4.2	$ 4.24
Average	**2.6**	**$ 3.95**
Standard deviation	**1.0**	**$ 0.20**

Other NYC Suburbs

Location	Distance from Penn Station (in miles)	Price
W. Cornell Med.	3.2	$3.89
Brooklyn	5.4	$ 3.29
Harlem	5.4	$ 3.79
Harlem	5.7	$ 3.69
Harlem	5.8	$ 3.69
Jackson Heights	6.6	$ 4.20
Jackson Heights	7.0	$ 4.19
Corona (near JH)	7.8	$ 4.19
La Guardia Airport	7.8	$ 4.09
Queens	9.2	$ 4.56
Bronx	10.2	$ 4.19
Queens	10.2	$ 4.39
Queens	11.0	$3.89
Queens	11.4	$ 4.56
Bronx	11.6	$ 4.39
Brooklyn	12.7	$ 3.69
Bronx	13.0	$ 3.49
Bronx	13.6	$3.99
Brooklyn	16.7	$ 3.99
JFK Airport	16.7	$ 4.19
Average	**9.6**	**$ 4.02**
Standard deviation	**3.8**	**$ 0.34**

Source: Personal phone survey during the week of July 17, 2011

Table 3
Big Mac Prices Relative to Manhattan (log)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Std. dev.
New York City												
Bronx	0.03	-0.04	0.00	-0.06	-0.02	0.17	0.32	0.24	0.10	0.14	0.07	0.12
Queens	-0.04	-0.03	-0.03	0.00	-0.07	0.03	0.09	0.03	0.07	0.06	-0.03	0.05
Average												***0.09***
United States												
Chicago	-0.27	-0.27	-0.26	-0.01	-0.08	-0.13	0.03	-0.09	-0.05	0.03	0.04	0.12
San Francisco	-0.15	-0.27	-0.15	-0.14	-0.07	-0.04	0.06	0.00	0.09	0.08	-0.05	0.11
Atlanta	-0.38	-0.38	-0.33	-0.29	-0.35	-0.30	-0.09	-0.14	-0.10	-0.14	-0.19	0.12
Average												***0.12***
International												
Australia	-0.73	-0.66	-0.55	-0.36	-0.33	-0.35	-0.09	-0.11	-0.01	0.05	0.15	0.29
Brazil	-0.64	-0.71	-0.78	-0.65	-0.37	-0.21	0.10	0.26	0.17	0.29	0.37	0.45
Canada	-0.38	-0.39	-0.38	-0.33	-0.27	-0.09	0.13	0.09	-0.01	0.08	0.17	0.23
China	-0.96	-0.90	-1.00	-0.95	-1.01	-0.97	-0.81	-0.70	-0.65	-0.64	-0.62	0.16
Germany/Euro	-0.31	-0.27	-0.08	0.01	0.03	0.09	0.24	0.36	0.28	0.17	0.15	0.22
Hong Kong	-0.82	-0.78	-0.79	-0.74	-0.82	-0.80	-0.75	-0.85	-0.72	-0.66	-0.78	0.05
Japan	-0.28	-0.44	-0.39	-0.33	-0.39	-0.44	-0.35	-0.35	-0.03	0.00	-0.04	0.17
Mexico	-0.28	-0.28	-0.39	-0.44	-0.30	-0.30	-0.19	-0.14	-0.37	-0.39	-0.44	0.10
Russia	-0.95	-0.92	-0.90	-0.80	-0.85	-0.66	-0.48	-0.38	-0.51	-0.46	-0.45	0.22
Thailand	-0.95	-0.90	-0.85	-0.80	-0.85	-0.79	-0.51	-0.69	-0.62	-0.53	-0.59	0.16
South Korea	-0.32	-0.28	-0.18	-0.18	-0.33	-0.27	-0.04	-0.15	-0.27	-0.26	-0.19	0.09
Switzerland	0.15	0.19	0.35	0.41	0.38	0.42	0.47	0.53	0.54	0.53	0.64	0.15
Sweden	-0.29	-0.22	0.10	0.19	0.18	0.27	0.40	0.54	0.35	0.58	0.59	0.30
United Kingdom	-0.10	-0.08	-0.03	0.04	-0.01	0.06	0.20	0.21	0.07	-0.05	-0.09	0.11
Average												***0.19***

Table 4
Average Price Volatility and Distance

	Level	Difference	Distance
	Std. dev.	**Std. dev.**	
New York City	**0.086**	**0.087**	**9**
United States	**0.094**	**0.098**	**1394**
International			
United States*	0.177	0.120	5240
Australia	0.209	0.106	8235
Brazil	0.348	0.150	7181
Canada	0.163	0.107	4072
China	0.150	0.111	5192
Germany/Euro	0.164	0.117	4101
Hong Kong	0.162	0.116	5885
Japan	0.186	0.156	5190
Mexico	0.191	0.134	5107
Russia	0.155	0.110	4413
Thailand	0.132	0.119	5705
South Korea	0.163	0.120	5374
Switzerland	0.138	0.110	4209
Sweden	0.217	0.152	3965
United Kingdom	0.163	0.101	4054
International average	**0.181**	**0.122**	**5195**
Correlation between Std. err. and distance	***0.682***	***0.466***	

* Standard deviation between U.S. and international locations

This table shows average time-series standard deviations in the real exchange rate (in log) between NYC, U.S., and international locations. The table shows this statistics in the level and difference of the log of the real exchange rate. The table also shows average distances between NYC, U.S., and international locations.

Table 5
Regression of Price Volatility on Distance and Borders

	Level				Difference			
	Coefficients	**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)	**Coefficients**	**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)
Distance (log)	0.017 *	(.002)			0.011 *	(.001)		
Border dummies								
Australia	0.042 *	(.016)	12	35039	-0.005	(.007)	-2	-4855
Brazil	0.191 *	(.016)	66547	1.76E+08	0.043 *	(.007)	55	145781
Canada	0.013	(.015)	2	3270	0.009 ***	(.007)	2	3345
China	-0.009	(.015)	-2	-3266	0.006	(.007)	2	3497
Germany/Euro	0.012	(.015)	2	3027	0.017 *	(.007)	5	7140
Hong Kong	0.002	(.015)	1	2373	0.010 ***	(.007)	3	5578
Japan	0.028 **	(.015)	5	9934	0.054 *	(.007)	165	315578
Mexico	0.034 *	(.015)	7	13655	0.031 *	(.007)	18	33012
Russia	-0.002	(.015)	-1	-1778	0.007	(.007)	2	3077
Thailand	-0.028 **	(.015)	-5	-10858	0.015 *	(.007)	4	8572
South Korea	0.004	(.015)	1	2465	0.016 *	(.007)	4	8687
Switzerland	-0.017	(.015)	-3	-4157	0.008	(.007)	2	3429
Sweden	0.068 *	(.015)	51	74982	0.054 *	(.007)	156	227613
United Kingdom	0.010	(.015)	2	2739	0.000	(.007)	1	1505
				2883				
City dummies								
Chicago	-0.012	(.015)			0.023 *	(.007)		
San Francisco	-0.026 **	(.015)			0.015 *	(.007)		
Atlanta	-0.029 *	(.015)			-0.006	(.007)		
R-squared	0.93				0.96			
Number of pairs	190				190			

Note: *,**,*** indicates that the coefficient is significantly different from zero at a 5%,10%,20% confidence level.

Table 6
Regression of Price Volatility on Distance and Borders, Adding a Constant

`

	Level				Difference			
	Coefficients	**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)	**Coefficients**	**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)
Constant	0.098 *	(.029)			0.074 *	(.013)		
Distance (log)	0.006 ***	(.004)			0.002 ***	(.002)		
Border dummies								
Australia	0.048 *	(.015)	3988	1.21E+07	0.000	(.007)	1	2560
Brazil	0.195 *	(.015)	3.62E+14	9.57E+17	0.046 *	(.007)	3.04E+09	8.03E+12
Canada	0.006	(.014)	3	4263	0.003	(.006)	4	6366
China	-0.010	(.015)	-6	-11452	0.006	(.006)	14	26414
Germany/Euro	0.007	(.014)	3	4885	0.013 *	(.006)	416	627768
Hong Kong	0.002	(.015)	1	3009	0.010 **	(.006)	135	292717
Japan	0.027 **	(.015)	109	208430	0.054 *	(.006)	1.15E+11	2.19E+14
Mexico	0.033 *	(.015)	280	526112	0.030 *	(.006)	1251172	2.35E+09
Russia	-0.004	(.015)	-2	-3438	0.005	(.006)	9	15105
Thailand	-0.029 *	(.015)	-148	-310368	0.014 *	(.006)	910	1909028
South Korea	0.003	(.015)	2	3271	0.015 *	(.006)	1312	2594704
Switzerland	-0.022 ***	(.014)	-41	-63113	0.005	(.006)	11	16624
Sweden	0.062 *	(.014)	44483	6.49E+07	0.050 *	(.006)	1.81E+10	2.63E+13
United Kingdom	0.006	(.014)	0	3851	-0.004	(.006)	-6	-8275
City dummies								
Chicago	-0.018	(.014)			0.018 *	(.006)		
San Francisco	-0.027 **	(.015)			0.014 *	(.006)		
Atlanta	-0.035 *	(.014)			-0.010 **	(.006)		
R-squared	0.66				0.58			
Number of pairs	190				190			

Note: *,**,*** indicates that the coefficient is significantly different from zero at a 5%,10%,20% confidence level.

Table 7
Regression of Price Volatility on Distance and Borders with a Dummy for each U.S. City^

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	Level					Difference				
	Coefficients		**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)	**Coefficients**		**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)
Distance (log)	0.016	*	(.003)			0.007	*	(.001)		
Border dummies										
Australia	0.049	*	(.019)	21	64340	0.012	***	(.008)	6	16857
Brazil	0.197	*	(.018)	247588	6.54E+08	0.059	*	(.008)	4232	1.12E+07
Canada	0.018		(.016)	3	4735	0.022	*	(.007)	21	31100
China	-0.004		(.017)	-1	-2407	0.021	*	(.007)	20	38509
Germany/Euro	0.017		(.017)	3	4423	0.030	*	(.007)	70	106288
Hong Kong	0.007		(.018)	2	3432	0.025	*	(.007)	36	77927
Japan	0.034	*	(.017)	8	16191	0.069	*	(.007)	17307	3.30E+07
Mexico	0.040	*	(.017)	12	22838	0.045	*	(.007)	595	1.12E+06
Russia	0.004		(.017)	1	2064	0.021	*	(.007)	20	32136
Thailand	-0.023	***	(.017)	-4	-8749	0.030	*	(.007)	68	143028
South Korea	0.009		(.017)	2	3571	0.031	*	(.007)	76	150266
Switzerland	-0.012		(.017)	-2	-3261	0.022	*	(.007)	23	35760
Sweden	0.073	*	(.017)	98	143190	0.067	*	(.007)	13109	1.91E+07
United Kingdom	0.016		(.017)	3	3979	0.014	*	(.007)	7	10460
City dummies										
Bronx	0.011		(.016)			0.033	*	(.007)		
Queens	0.007		(.016)			0.013	*	(.007)		
Chicago	-0.007		(.016)			0.036	*	(.007)		
San Francisco	-0.020		(.017)			0.030	*	(.007)		
Atlanta	-0.024	***	(.017)			0.007		(.007)		
R-squared	0.93					0.97				
Number of pairs	190					190				

^ Except Manhattan for identification.

Note: *,**,*** indicates that the coefficient is significantly different from zero at a 5%,10%,20% confidence level.

Table 8
Regression of Price Volatility on Distance and Borders, using NYC Average

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	Level				Difference			
	Coefficients	**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)	**Coefficients**	**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)
Distance (log)	0.013 *	(.003)			0.007 *	(.001)		
Border dummies								
Australia	0.054 *	(.019)	62	186542	0.011 ***	(.008)	4	13282
Brazil	0.202 *	(.019)	4786423	1.26E+10	0.059 *	(.008)	3649	9.64E+06
Canada	0.021	(.017)	5	7170	0.021 *	(.007)	18	26264
China	0.008	(.018)	2	3542	0.022 *	(.007)	21	40474
Germany/Euro	0.025 ***	(.017)	7	9822	0.030 *	(.007)	62	92983
Hong Kong	0.030 **	(.018)	10	20940	0.028 *	(.008)	47	102562
Japan	0.047 *	(.018)	36	68822	0.070 *	(.007)	17562	3.35E+07
Mexico	0.061 *	(.018)	101	189344	0.045 *	(.008)	537	1.01E+06
Russia	0.011	(.017)	2	3666	0.021 *	(.007)	19	31413
Thailand	-0.011	(.018)	-2	-4793	0.030 *	(.007)	66	138320
South Korea	0.029 **	(.018)	9	18605	0.030 *	(.007)	64	126273
Switzerland	-0.002	(.017)	-1	-1836	0.023 *	(.007)	25	38743
Sweden	0.077 *	(.017)	345	502853	0.068 *	(.007)	12171	1.78E+07
United Kingdom	0.034 *	(.017)	13	19537	0.013 **	(.007)	6	8994
City dummies								
Chicago	0.003	(.017)			0.033 *	(.007)		
San Francisco	-0.006	(.018)			0.031 *	(.008)		
Atlanta	-0.014	(.017)			0.005	(.007)		
R-squared	0.93				0.97			
Number of pairs	153				153			

Note: *,**,*** indicates that the coefficient is significantly different from zero at a 5%,10%,20% confidence level.

Table 9
Multiple Regressions of Price Volatility on Distance and the Border

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	Level					Difference				
	Coefficients	**Std. err.**	**R-squared**	**Implied border** (in miles)	**Implied PW* border** (in miles)	**Coefficients**	**Std. err.**	**R-squared**	**Implied border** (in miles)	**Implied PW* border** (in miles)
Distance (log) with										
Australia	0.009 *	(.001)				0.011 *	(.001)			
Brazil	0.009 *	(.001)				0.012 *	(.001)			
Canada	0.009 *	(.001)				0.012 *	(.001)			
China	0.010 *	(.001)				0.012 *	(.001)			
Germany/Euro	0.009 *	(.001)				0.012 *	(.001)			
Hong Kong	0.011 *	(.001)				0.012 *	(.001)			
Japan	0.010 *	(.001)				0.011 *	(.001)			
Mexico	0.011 *	(.002)				0.012 *	(.002)			
Russia	0.009 *	(.001)				0.012 *	(.001)			
Thailand	0.009 *	(.001)				0.011 *	(.001)			
South Korea	0.011 *	(.001)				0.012 *	(.001)			
Switzerland	0.009 *	(.001)				0.012 *	(.001)			
Sweden	0.009 *	(.001)				0.012 *	(.001)			
United Kingdom	0.010 *	(.001)				0.012 *	(.001)			
Border dummies										
Australia	0.133 *	(.013)	0.98	1.84E+06	6.29E+09	-0.025 **	(.013)	0.96	-10	-33301
Brazil	0.290 *	(.013)	0.99	2.51E+13	4.74E+16	0.036 *	(.015)	0.96	22	40986
Canada	0.093 *	(.011)	0.97	21450	5.88E+06	0.013	(.014)	0.94	3	794
China	0.026 *	(.011)	0.98	15	35882	-0.012	(.014)	0.95	-3	-7080
Germany/Euro	0.063 *	(.012)	0.98	795	1.30E+06	0.003	(.013)	0.96	1	2078
Hong Kong	-0.018	(.016)	0.94	-5	-15216	-0.027 *	(.013)	0.96	-10	-30224
Japan	0.055 *	(.01)	0.98	295	697345	0.020 ***	(.012)	0.97	6	13578
Mexico	0.030 **	(.016)	0.93	16	10742	0.033 *	(.015)	0.95	16	10686
Russia	0.063 *	(.012)	0.97	741	1.37E+06	-0.004	(.016)	0.94	-1	-2588
Thailand	-0.001	(.012)	0.97	-1	-3438	-0.017 **	(.013)	0.96	-4	-14145
South Korea	-0.004	(.014)	0.95	-2	-3723	0.002	(.014)	0.95	1	2975
Switzerland	0.017 ***	(.01)	0.97	6	9757	-0.011	(.014)	0.95	-3	-4147
Sweden	0.145 *	(.012)	0.99	6073737	9.71E+09	0.040 *	(.014)	0.96	30	48343
United Kingdom	0.002	(.013)	0.96	1	1792	-0.011	(.013)	0.95	-3	-3719
Number of pairs	21					21				

* Using average distance with US city pairs

Note: *,**,*** indicates that the coefficient is significantly different from zero at a 5%,10%,20% confidence level. City coefficients omitted for clarity.

Table 10
Regression of Price Volatility on Distance and Borders
using EIU Data (Fast food snack: hamburger, fries and drink) from 1995 to 2005

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	Level					Difference				
	Coefficients		**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)	**Coefficients**		**Std. err.**	**Implied border** (in miles)	**Implied PW border** (in miles)
Distance (log)	0.023	*	(.003)			0.026	*	(.003)		
Border dummies										
Australia	0.012		(.018)	2	5057	-0.017		(.019)	-2	1574
Brazil	0.257	*	(.018)	86526	2.29E+08	0.083	*	(.019)	26	68596
Canada	-0.012		(.016)	-2	-2595	-0.027	***	(.017)	-3	-4228
China	0.023	***	(.017)	3	5208	0.046	*	(.018)	6	11307
Germany/Euro	-0.011		(.016)	-2	-2427	-0.015		(.017)	-2	-2683
Hong Kong	0.041	*	(.017)	6	13488	0.045	*	(.018)	6	12524
Japan	0.025	***	(.017)	3	5897	0.039	*	(.018)	5	8726
Mexico	-0.024	***	(.017)	-3	-5481	-0.017		(.018)	-2	-3603
Russia	0.118	*	(.017)	187	303390	0.206	*	(.017)	3034	4.93E+06
Thailand	-0.008		(.017)	-1	-2994	0.012		(.018)	2	3296
South Korea	0.059	*	(.017)	14	27420	0.016		(.018)	2	3725
Switzerland	0.000		(.016)	1	1533	-0.015		(.017)	-2	-2770
Sweden	0.004		(.016)	1	1704	-0.016		(.017)	-2	-2766
United Kingdom	-0.019		(.016)	-2	-3522	-0.023	***	(.017)	-2	-3714
City dummies										
Chicago	-0.015		(.016)			-0.044	***	(.017)		
San Francisco	0.083	*	(.017)			0.087	*	(.018)		
Atlanta	-0.035	*	(.017)			-0.049	*	(.017)		
R-squared	0.97					0.97				
Number of pairs	153					153				

Note: *,**,*** indicates that the coefficient is significantly different from zero at a 5%,10%,20% confidence level.