The LoP Game:
BigMac versus Fortnite

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Abstract

We analyze the law of one price (LoP) based on BigMac and Fortnite prices. We find a positive but less than a perfect correlation between the over-/undervaluations of the two indices. While LoP holds for the Fortnite data, it does not hold for the BigMac data.

Keywords: Fortnite, BigMac, law of one price

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1 Introduction

Parents all over the world are scared of the excess gaming behavior of their children and would like to get them out of the 'Fortnite trap'. Kids do not only spend a lot of time, but also a lot of money on items from the in-game-shop.[1] The shop offers a large variety of uniforms ('skins'), parachutes ('gliders'), dance moves ('emotes'), and even a battle pass, which can be bought by using a Fortnite specific virtual currency called *V-Bucks*. In order to go shopping, the national currency has to be converted into V-Bucks.

We study how V-Buck prices are set in a large number of national currencies and compare the pricing with the well known BigMac index. We expect that there is a positive correlation between the under-/overvaluations measured by the BigMac and the Fortnite index. Since V-Bucks are virtual goods, we also hypothesize that the degree of under-/overvaluation is lower as compared to that of the BigMac. In fact, arbitrage in Fortnite V-Bucks should be much easier than in BigMacs, which contains several non-tradable components. A gamer could use a VPN client and mislead Fortnite to believe, that he or she is, for example, in Indonesia where 1,000 V-Bucks cost 100,000 Rupiah = \$7.04 instead of \$9.99 in the US (-29.5%).

Our empirical results for a sample of 26 countries support our hypotheses. The under-/overvaluation measured in mid-2019 using V-Bucks is significantly smaller (in absolute values) than the under-/overvaluation implied by the BigMac prices. Moreover, the under-/overvaluation of V-Bucks is not significantly different from zero on average across countries. It thus appears that in the online world of video games, the border is much less wide than in the real-world (on the latter, see Engle/Rogers 1996).

The paper is structured as follows: Section 2 reviews the literature. Section 3 describes the data set and the empirical results. Section 4 concludes.

[1] In the last two years, Fortnite was the best-selling video game which generated \$2.4 bn (2018) and \$1.8 bn. (2019) in revenues (SuperData 2019 and 2020).

2 Some Remarks on the Literature

Assuming free trade, no transaction costs, complete transparency for all agents, and homogeneous goods (that is, geographical preferences, preferences in time, personal preferences, and goods have the same characteristics) then the prices in different countries, which have their own respective currencies, have to be the same. The law of one price (LoP) holds.

A popular way of studying the LoP is to use the BigMac index developed by the *The Economist* journal in the 1980s. Advantages of using the BigMac index for studying the LoP are that a BigMac is a more or less homogeneous good around the world (no differences in quality) and preferences can be assumed to be relatively homogeneous in different countries. However, the BigMac itself is *not* an internationally traded good. As a result, the BigMac does not fulfill all the characteristics mentioned above. Thus, it is not surprising that the LoP – in its pure version – is frequently rejected in the BigMac literature (for recent studies, see, e.g., Parsley/Wei 2007, Clements et al. 2012).

In an early study based on BigMac data, Click (1996) finds that the LoP does not hold, and that the country-specific deviations can be explained by the Balassa-Samuelson argument: *Countries with a lower GDP per capita level have lower price levels.* Cumby (1996) reports that the BigMac helps to explain subsequent changes in the exchange rate. Pakko/Pollard (2003, p. 22) conclude that the BigMac price is a *"composite of tradable commodities and non-tradable service content"*. Parsley/Wei (2007) also emphasize that it is important to disentangle a BigMac into its tradable and non-tradable components, where they find that the non-traded components display greater cross-country price dispersion than the traded components.

3 Empirical Analysis

A numerical example helps to refresh the BigMac concept: A BigMac is sold for 13.99 TRY in Turkey and 5.74 USD in the United States, which

gives an equilibrium exchange rate of $e^* = 13.99$ TRY / 5.74 USD = 2.44 TRY/USD. By computing the relative difference between the equilibrium and the current exchange rate, the degree of undervaluation is determined: $(e^* - e)/e = (2.44 - 5.72)/5.72 = -57.4\%$.

By the same approach, we compute the degree of over-/undervaluation using Fortnite prices. 1000 V-Bucks are sold for 44.99 TRY in Turkey and for 9.99 USD in the United States, leading to an equilibrium Fortnite-based exchange rate of $e_f^* = 44.99/9.99 = 4.50$. The resulting degree of undervaluation is $(e_f^* - e)/e = (4.50 - 5.89)/5.89 = -23.5\%$. In this example, the degree of undervaluation (in absolue value) is smaller using Fortnite prices as compared to BigMac prices.

In order to set up our data set, we used a press release of the Fortnite developer *Epic* (2019). We then cross-checked the data by visiting the Internet pages of national *PlayStores*.[2]

Figure 1 displays the degree of under-/overvaluation by country for the BigMac and the Fortnite data. Results show that the BigMac prices imply strong undervaluations except in the case of Switzerland. In contrast, the results we obtain when using V-Bucks do not show a clear-cut pattern across countries. There are several overvaluations, but also several undervaluations. In absolute terms, the degree of misalignment based on V-Bucks is smaller than the one based on BigMac prices, supporting our hypothesis that the extent of misalignment is lower for the virtual good (V-Bucks) compared to the BigMac.

– Include Figures 1 about here. –

Table 1 depicts the summary statistics of the data. The median and mean of the misalignment based on the BigMac prices are negative and much larger

[2]By also visiting the Internet pages of the PlayStore shop, we were able to increase the list of countries in our sample data to include Brazil, Croatia, Indonesia, and Romania. We also realized that in the PlayStores of some countries – for example, Mexico – prices are set in U.S. dollars. We decided to include only countries where prices are set in local currency. The BigMac data (07/2019) were taken from the *Economist's* webpage, and exchange-rate data from PACIFIC Exchange Rate Service.

(in absolute values) than the median and the mean of the misalignment based on V-Bucks data. A similar picture arises when we turn to the absolute values of the over-/undervaluations. Similarly, the minimum of the BigMac data is larger (in absolute value) than the minimum based on the V-Bucks data. The maximum based on the V-Bucks data, in turn, is larger than the maximum based on the BigMac data.

– Include Table 1 about here. –

Applying t-tests shows that the null hypothesis that the difference in means is equal to zero can be rejected ($t = -7.17$, p-value < 0.01). When we consider the absolute overvaluations, we can reject the null hypothesis that the difference in means (BigMac minus Fortnite) is smaller than zero ($t = 6.37$, p-value < 0.01). Moreover, we cannot reject the null hypothesis that the mean of the misalignment based on V-Bucks is zero ($t = -0.08$, p-value $= 0.93$). Hence, we cannot reject the LoP on average across countries for the Fortnite data. In contrast, we reject the the null hypothesis of a zero mean misalignment for the BigMac data ($t = -8.72$, p-value < 0.01).

– Include Table 2 about here. –

Table 2 presens the results of estimating a regression equation by the ordinary-least-squares technique for the misalignment based on the V-Bucks data on a constant and the misalignment based on the BigMac data. In order to test the stability of the results based on a 1,000 V-Buck package, we also present evidence for other package sizes. The estimates for the slope parameter are around $\hat{\beta} = 0.3$ and significantly smaller than 1. Hence, there is a positive association in the data, but no one-to-one relationship. The overall fit (that is, R^2 statistic) of the regression models is between 0.17 and 0.19. Hence, the two price indices vary substantially.

4 Conclusions

We have compared misalignments (that is, over-/undervaluation) implied by BigMac data and Fortnite data and find a positive but less than a perfect association between the misalignments. We have rejected the LoP for the

BigMac data, but not for the Fortnite data. One interpretation of our results is that, because Fortnite creates a virtual product, arbitrage possibilities are easier to exploit than for a BigMac.

Another interpretation is based on the observation that the variable cost of the game developer Epic to create V-Bucks (or the virtual good that can be bought for this amount) is relatively low. Variable costs are negligible when a standardized virtual good is created. Furthermore, the cost to create a virtual good is almost completely denominated in US-dollars and not in national currency. While the Balassa-Samuelson argument is convincing for misalignments in the BigMac, it does not hold for the Fortnite good.

Finally, it is worth emphasizing that Fortnite was firstly introduced in 2017. Hence, the time period since its introduction is much shorter than the time period during which the BigMac has been around. Because deviations from the LoP are to some extent due to exchange-rate fluctuations, a shorter time period since introduction implies a shorter time period for deviations from LoP to build up.

In future research, it is interesting to collect data for a longer time period and to estimate panel-data models in order to inspect in more detail the results we have reported in this research.

References

Chen C-F, Shen C-H, and Wang C-A. (2003): Does PPP hold for Big Mac price or consumer price index? Evidence from panel cointegration. Economics Bulletin, Vol. 6, 1 – 15.

Clements, K. W., Lan, Y., and Seah, S. P. (2012): The Big Mac Index two decades on: An evaluation of Burgernomics. International Journal of Finance and Economics, Vol. 17(1), 31 – 60.

Cumby, R.E. (1996): Forecasting exchange rates and relative prices with the hamburger standard: Is what you want what you get with McParity? NBER Working Paper 5675, Cambridge, Mass.

Click, R. (1996): Contrarian MacParity. Economics Letters, Vol. 53(2), 209 – 212.

Engle, C., and Rogers, J.H. (1996): How wide is the border? American Economic Review, Vol. 86 (5), 1112 – 1125.

Pakko, M. R., and Pollard, P. S. (2003): Burgernomics: A Big Mac^{TM} guide to purchasing power parity. The Federal Reserve Bank of St. Louis Review, November/December 2003, 9 – 28.

Parsley D, and Wei, S. (2007): A prism into the PPP puzzles: The micro-foundations of Big Mac real exchange rates. Economic Journal, Vol. 117 (523), 1336 – 1356.

SuperData (2019): 2018 Year in Review – Digital Games and Interactive Media. SuperData – A Nielsen company.

SuperData (2020): 2019 Year in Review – Digital Games and Interactive Media. SuperData – A Nielsen company.

Table 1: Summary Statistics

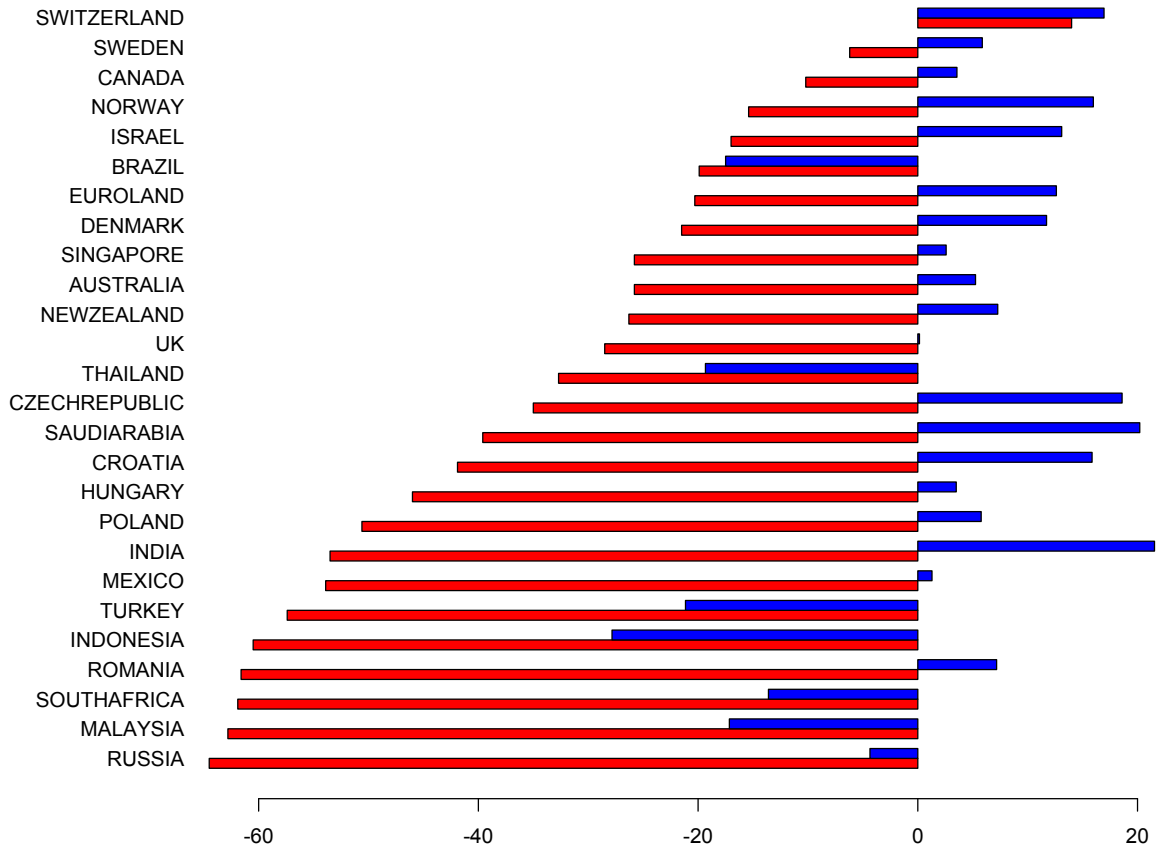
	minimum	1st quartile	median	mean	3rd quartile	maximum
Big Mac	-64.50	-53.80	-33.85	-35.57	-20.60	14.00
abs(Big Mac)	6.20	20.60	33.85	36.65	53.80	64.50
Fortnite	-29.53	-5.34	1.63	-0.23	9.99	20.09
abs(Fortnite)	0.17	1.88	9.76	10.72	17.67	29.53

Table 2: Regression Results

	Model 1	Model 2	Model 3	Model 4
	1,000 V-Bucks	2,500 V-Bucks	4,000 V-Bucks	10,000 V-Bucks
Intercept	.0968*	.1042*	.1008*	.1049*
	(.0516)	(.0530)	(.0509)	(.0547)
Slope	.2788**	.2945**	.2873**	.3243**
	(.1259)	(.1293)	(.1239)	(.1322)
R^2	.1697	0.1778	0.1771	0.1941
Obs	26	26	26	26

Note: Standard errors in parentheses. ** (*) denote significance on a 5 % (10 %) level.

Figure 1: Under-/Overvaluations by Countries



Note: BigMac = red. Fortnite = blue. Undervaluation of currency against USD = negative number.