Estimating the value of a CHIP.*

January 18, 2023

This note presents a conceptual framework to quantify the baseline value of the CHIP currency tied to the global average of one hour of unskilled work. Econometric estimates using panel data from 89 world countries over the period 1992-2019 suggest the CHIP value of $2.53 per hour.

1 Introduction

The contemporary post-Bretton-Woods monetary system is increasingly criticized for its excessive reliance on several large central banks, which often pursue opaque and discretionary policies, poor handling of inflation, and inability to embrace modern technologies, such as cryptographic currencies. Responding to these challenges, Bateman (2022) proposes a novel money system anchoring means of payment to the value of time and using complementary currency nicknamed CHIP.[1] Bateman argues that this novel system will offer a number of important improvements, including

1. maintaining a consistent value over time,
2. offering better value and convenience to consumers,
3. exhibiting greater resistance to theft and unethical manipulation by business or government, and
4. being compatible with sound and sustainable economic principles, including free will and choice.

For purposes of standardization, Bateman suggests indexing (or linking) the value of a CHIP to one hour of basic or unskilled work. The purpose of this research note is to quantify the baseline value of the CHIP. The first section of the note uses the theory of economic growth to conceptualize the CHIP value as a distortion-free value of unskilled labor compensation at the global scale.

*This note was prepared by a Ph.D. Economist, whose identity is not disclosed in order to comply with the terms of their present full-time employment. The author thanks Kyle Bateman, David Spencer, Christian Vom Lehm, and the anonymous reviewer for their helpful comments. All remaining errors are the author's own.

[1]This acronym originally came from "Credit Hour In Pool."

The second section outlines the empirical approach to apply this definition to the panel data of 89 world countries over the period 1992-2019, collected from different public sources. The third section describes econometric estimates, including the main result of pinning the CHIP value to \$2.53 per hour. Finally, the last section concludes and suggests several venues for future work.

2 Theory

This section presents a simple economic framework whose core assumptions are based on a Solow-Swan growth modeling framework (Solow 1956, Swan, 1956, Acemoglu 2009). The model deviates from this framework by allowing for labor skill and human capital differentiation (Hanushek and Kimko, 2000). We assume that each country is an open economy (i.e., there are no barriers to labor and capital migration inside and outside the country), producing and consuming a unique final good. The economy is in the steady state equilibrium, so all decisions are solutions to the static problem.

2.1 Households (Labor Supply)

The economy is inhabited by a large number of households (or economic agents), which supply labor hours, L, inelastically; there is no leisure. Within each country, agents have different labor skills, ranking from unskilled to highly skilled labor. Let a_i be the labor skill level of a household type i with $a_1 = 1$ be the skill level of the highest skilled labor category. Countries also differ in terms of average level of households' human capital (e.g., average educational attainment), which we denote by h. Under this assumption, the total value of the efficient (i.e., skill- and human capital- adjusted) labor in a country j is given by:

$$L_{s,j} = h_j \sum_{i}^{N} a_i L_{i,j}, \tag{1}$$

where N is the number of household types according to their skill levels.

2.2 Firms (Labor Demand)

We assume that all firms in the economy are small, operate in a perfectly competitive environment, and have access to the same production function for the final good. The supply side of the economy can then be described by a representative firm and a production function. We assume that economy's production function is the Cobb-Douglas function[2]:

$$Y_j = K_j^{\alpha_j} L_{s,j}^{1-\alpha_j}, \tag{2}$$

[2] The Cobb-Douglas production function is the most common example of a production function used in macroeconomics (see, e.g., Acemoglu 2009).

where, Y is the output of the good in the economy, K is the aggregate capital endowment in the country owned by households, and α is the capital compensation share in the economy. Let $y = Y/L_s$ and $k = K/L_s$ be the amount of output and capital per unit of efficient labor. Then the economy's production function per unit of efficient labor becomes

$$y_j = k_j^{\alpha_j}. \tag{3}$$

2.3 Labor Market Equilibrium

Because the economy's labor supply is inelastic, the labor market equilibrium is determined by the labor demand side resulting from firms' profit maximization problem:

$$\pi_j = K_j^{\alpha_j} L_{s,j}^{1-\alpha_j} - w_{s,j} L_{s,j}, \tag{4}$$

where π is the firm's profit and w is the unit cost of efficient labor (or the wage rate per unit of efficient labor). A firm's profit maximization requires

$$\frac{\partial \pi_j}{\partial L_{s,j}} = 0 \Longrightarrow (1-\alpha_j)\, K_j^{\alpha_j} L_{s,j}^{-\alpha_j} = (1-\alpha_j)\, k_j^{\alpha_j} = w_{s,j} = \bar{w_s}. \tag{5}$$

Equation (5) is the standard result from the economic theory, which implies that labor compensation should equal the value of the marginal product of efficient labor. In the open economy equilibrium, wages are equalized across countries (Samuelson, 1948), so all wages equal the global marginal product of efficient labor, $\bar{w_s}$.

2.4 The value of CHIPS for labor compensation

Let us define the distortion factor, $\theta_j \equiv \frac{(1-\alpha_j)k_j^{\alpha_j}}{w_{s,j}}$, as the ratio of the marginal product of efficient labor to efficient (i.e., skill-weighted) labor compensation in the economyUnder the model assumptions, the distortion factor should be equal to one. In the real world, model assumptions will unlikely hold given barriers to labor and capital flows, regulatory distortions (e.g., minimum wage), and other market failures (such as, e.g., market power). This implies that the distortion factor will also differ from one. In practical terms, the distortion factor implies how much each economy's labor should be compensated (or taxed) to restore the labor market equilibrium defined by equation (5). We can then define the distortion-free value of labor compensation as the product of the distortion factor and the observed efficient labor compensation in the economy:

$$w_{s,j}^e = \theta_j w_{s,j}. \tag{6}$$

Combining equation (6) with the definition of a CHIP (Bateman, 2022), we define the value of the CHIP as the distortion-free value of unskilled labor compensation.

3 Estimation Approach

3.1 Method

We estimate the economies' production function using the following empirical specification:

$$\ln y_{j,t} = \alpha_j \ln k_{j,t} + \epsilon_{j,t}, \tag{7}$$

where α_j is the vector of coefficients (or country fixed effects) to be estimated. Equation (7) is estimated by the ordinary least squares (OLS) with fixed effects estimation method and is implemented in R statistical software using *fixest* package, *feols* function.[3]

3.2 Data

We rely on three open data sources to estimate the CHIPS value of labor. The data on the labor input (measured as total weekly hours by employed population in a country) and labor compensation (in USD) come from the ILOSTAT *Labour Force Statistics* and *Wages and Working Time Statistics* databases.[4] The ILOSTAT data differentiates labor input across nine International Standard Classification of Occupations 2008 (ISCO-08) categories[5]: (i) managers, (ii) professionals, (iii) technicians and associate professionals, (iv) clerical support workers, (v) service and sales workers, (vi) skilled agricultural, forestry, and fishery workers, (vii) craft and related trades workers, (viii) plant and machine operators, and assemblers, and (ix) elementary occupations.[6] To construct the efficient labor input, we assume that managers are the highest skill category. We calculate the skill-level of in each remaining category as the ratio of wages in this category relative to the managers. Figure 1 shows the average skill levels of each labor category across our data sample. We calculate the average wage in each country as an average of wages across different types of labor weighted by the total number of labor hours in each labor category.

The data on output, capital input, and human capital index come from the Penn World Tables (PWT) 10.0 database (Feenstra and Timmer, 2015). For measures of output, we use (i) real GDP at constant national prices (in a million of 2017 USD, variable *rgdpna*) and (ii) output-side real GDP at current purchasing power parities (PPPs, in a million 2017 USD, variable *cgdpo*). For measures of capital input, we use (i) capital stock at constant national prices (in a million of 2017 USD, variable *rnna*) and (ii) capital stock at current PPPs (in a million 2017 USD, variable *cn*). For a measure of human capital, we use the PWT human capital index (variable *hc*), based on years of schooling

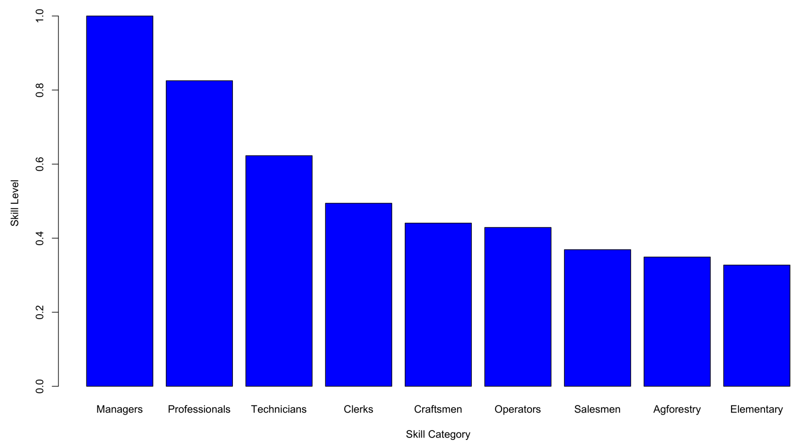
[3] see `https://www.rdocumentation.org/packages/fixest/versions/0.8.4/topics/feols`

[4] see `https://ilostat.ilo.org/data/`

[5] see `www.ilo.org/public/english/bureau/stat/isco/`

[6] We exclude the armed forces and occupations not elsewhere classified. Some countries use older ISCO classifications (e.g., ISCO-68 and ISCO-88), which are converted into ISCO-08 using the correspondence tables provided by ISCO.

Figure 1: Average skill level by labor skill category



and returns to education. We distinguish between output and capital stock estimates using market exchange rates and PPPs because there is no consensus in the economics literature about which measure more adequately represents the supply side of the economy, especially in the poor countries. While PPPs better approximate values of tradable homogenous goods, they are also biased due to their poor ability to measure differences in quality across goods and services. This may result in a mechanical overvaluation of consumption bundles because the relative prices used for valuing the bundles differ from the transacted prices (Dowrick and Akmal, 2005). As physical capital input is poorly tradable on the secondary market due to significant sunk costs and its quality is difficult to measure, our preferred specification is using measures in constant national prices in millions of 2017 USD.

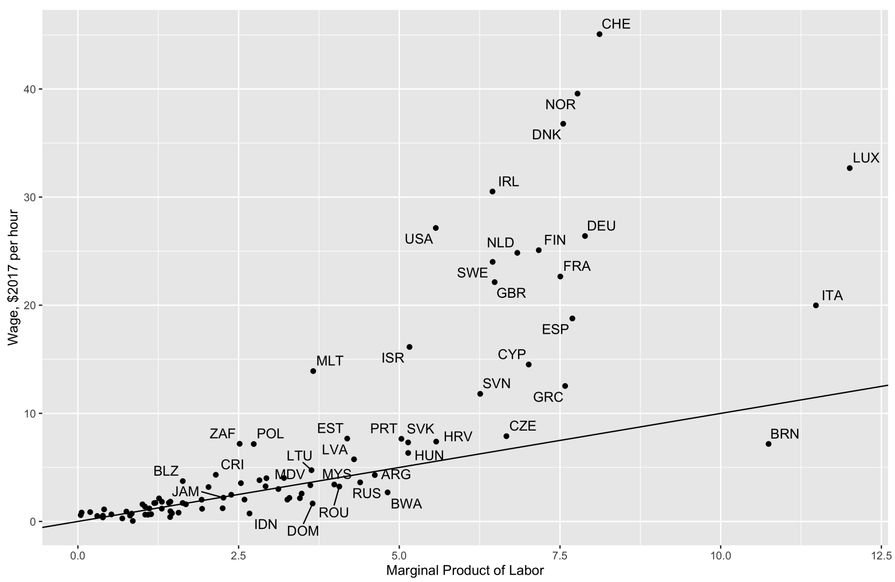
Finally, we use the US GDP implicit price deflator data from the St. Louis FRED database[7] to convert nominal U.S. dollar-denominated wages to their real values. After removing extreme outliers and observations with obvious measurement errors, the final dataset for estimating the marginal product of labor is an unbalanced panel comprising 2165 observations and covering 98 world countries from 1970 to 2019. Combining the marginal product of labor estimates' data with the wage data yields the final 451 observations covering 89 countries from 1992-2019.

4 Results

Figure 2 plots the estimated average marginal product of efficient labor versus real wage across countries in our sample. The solid line in Figure 2 s a

[7]see `https://fred.stlouisfed.org/series/USAGDPDEFAISMEI`

Figure 2: Estimated marginal product of efficient labor vs. real wage



45-degree line along which local labor markets show no distortions, and the country's marginal product of efficient labor equals its real wage. If the data point lies above the 45-degree line, the country's marginal product of efficient labor is less than the real wage. That is, workers in these countries are overpaid relative to market equilibrium. Conversely, if the data point lies below the 45-degree line, the country's marginal product of efficient labor exceeds real wage, and workers in these countries are underpaid relative to market equilibrium. We see that in most world countries, data points lie close to the 45-degree line, which indicates their labor markets are relatively undistorted.[8] However, we also see that real wage greatly exceeds the marginal product of efficient labor in most OECD economies. This could be due to market distortions from minimum wage regulations, greater bargaining power of labor unions, or labor market segmentation leading to certain skill shortages and excessive wages. This could also be due to unobserved technological differences that could affect the marginal product of labor estimates, such as the productivity of capital in the information and communication services sector, which accounts for most of the productivity improvements in developed economies (Jorgenson, Ho, and Stiroh, 2008). Finally, estimates can be biased in developing countries with a large informal sector, where many small, unregistered establishments are missing from the ILO sample frame.[9].

[8] Several countries (Brunei, Italy, Luxembourg) are outliers with unexpectedly large labor productivities, which are likely due to measurement errors.

[9] `https://ilostat.ilo.org/resources/concepts-and-definitions/description-wages-and-working-time-statistics/`

Table 1 shows summary statistics for calculated distortion factors (DF) based on the formula in section 2.4 using the following definitions:

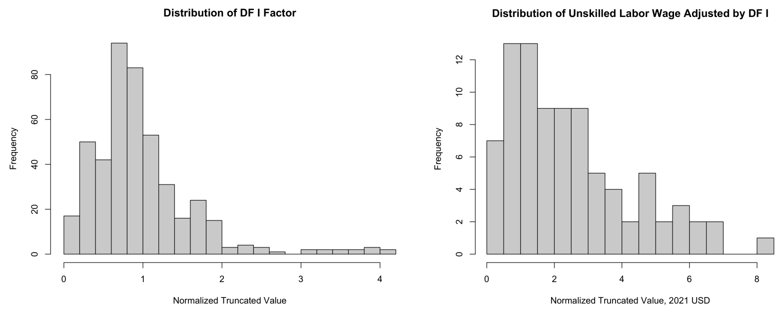
- DF I (preferred specification): the ratio of estimated marginal product of labor to real wage where labor is measured in total effective hours worked, using measures of output and capital in constant national prices in millions of 2017 USD.
- DF II (assuming $\alpha_j = 0$ or marginal product of labor is simply efficient labor): the ratio of the country's 'efficient' wage (i.e., the wage weighted by productivity of each worker category, where the productivity is measured by the relative wage of a given worker category to managers) to its average wage in a given year.
- DF III (assuming $a_i = 1$ or skill productivities are similar across all labor categories): the ratio of estimated marginal product of labor to real wage where labor is measured in total hours worked (i.e., a simple summation of labor hours across all labor categories), using measures of output and capital in constant national prices in millions of 2017 USD.
- DF IV (assuming PPP conversion): the ratio of estimated marginal product of labor to real wage where labor is measured in total effective hours worked, using measures of output and capital in current PPPs in millions of 2017 USD.

Table 1: Summary Statistics for CHIPS conversion factors

Distortion Factor	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
DF I	451	1.05	1.17	0.05	0.61	1.2	18.57
DF II	451	1.24	0.18	0.94	1.13	1.32	2.84
DF III	446	0.52	0.63	0.03	0.26	0.62	10.35
DF IV	451	1.08	1.09	0.05	0.61	1.24	15.89

We see that, consistent with the evidence in Figure 2, the average distortion factor using preferred specification is close to 1, which indicates that labor markets are globally efficient. However, there is a significant dispersion across countries, with the distribution of the DF I factor exhibiting a long right tail (Figure 3, left panel). The average distortion factor assuming PPP conversion (DF IV) is very similar to our preferred specification, which indicates that using PPP rather than nominal exchange rate conversion has a small impact on the estimated DF factor value. Alternative definitions using more restrictive assumptions result in biased estimates of the distortion factor. The DF II factor is, on average, greater than one and has a much smaller dispersion than other measures. Assuming away capital in a country's production thus *overestimates* the value of the marginal product of labor. The DF III factor is, on average, less than one and twice smaller than our preferred estimate of the DF factor.

Figure 3: Distribution of DF I factor and adjusted wages across countries



Assuming that skill productivities are similar across all labor categories thus *underestimates* the value of the marginal product of labor.

We are now ready to answer the main question of this research note: how large countries' unskilled labor (elementary occupations) wages would be if market distortions were eliminated? Our preferred measure, DF I, offers the average local value of labor compensation of \$2.5 per hour for unskilled labor (Figure 3, right panel), whose values range between \$0.047 (Rwanda) to \$8.06 (Italy). Finally, we need to obtain the global value of labor compensation (i.e., when labor mobility barriers are eliminated). To do so, we calculate the average value of labor compensation, weighted by each country's contribution to global GDP. This gives us the final value of unskilled labor compensation that underpins the CHIP index: \$2.53 per hour.

5 Conclusions and Directions for Future Work

This note sets an important milestone in quantifying the value of a novel currency, the CHIP. Using a conceptual framework engrained in the theory of economic growth, we define the baseline CHIP value as a distortion-free value of unskilled labor compensation at the global scale. Applying this framework to the panel data of 89 world countries from 1992-2019, collected from different public sources, yields econometric estimates of the CHIP value at \$2.53 per hour. While this number may seem low in the context of developed economies (estimated value is roughly eight times smaller than unskilled labor compensation in the United States), it is not surprising if put into the context of the global unskilled labor force, dominated by low and middle-income countries. While reasonably accurate, estimates in this note are only the first attempt to tackle the complex problem of calculating the base value of the CHIP. As with all new concept developments, several improvements can be made to obtain better estimates, especially for developed economies where larger discrepancies between actual unskilled wages and theoretical predictions have been found.

They include, but are not limited to (i) endogenizing labor supply decisions in the context of labor-leisure choice across time (see, e.g., Turnovsky, 2000), (ii) explicitly incorporating technological differences, especially the value of information and communication technology capital across countries (Jorgenson, 2005), and addressing measurement errors affecting the quality of labor productivity and earnings data related to regional disparities and prevalence of informal economy.

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