Labor Market Dynamics in Developing Economies: the Role of Subsistence Consumption*

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Abstract

Motivated by the recent empirical evidence on a strong negative relationship between the income-level and hours worked across countries (Bick, Fuchs-Schündeln, and Lagakos (2018)), this paper establishes new stylized facts on labor market dynamics in developing economies. First, the response of hours worked (and employment) to a permanent technology shock—identified by a structural VAR model with long-run restrictions—is smaller in developing economies than in advanced economies. Second, the level of income per capita is strongly and robustly associated with the relative variability of hours worked and consumption to output across countries. We build a simple RBC model augmented with subsistence consumption to explain the set of new empirical findings. The minimal departure from a standard RBC model allows us to account for the salient features of business cycle fluctuations in developing economies, including their distinct labor market dynamics.

JEL classification: E21; E32; F44; J20

Keywords: Business cycles; Developing economies; Subsistence consumption; Labor market dynamics; Long-run restrictions

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1 Introduction

Business cycles in developing economies are often characterized by higher variability of consumption relative to output, together with countercyclical net exports and interest rates (see Neumeyer and Perri (2005) and Aguiar and Gopinath (2007) among others). To explain such distinct features from business cycles in advanced economies, the existing studies on developing economies often emphasize the role of trend productivity shocks (Aguiar and Gopinath (2007); Boz, Daude, and Durdu (2011); Naoussi and Tripier (2013)) or financial frictions (Neumeyer and Perri (2005); Uribe and Yue (2006); Garcia-Cicco, Pancrazi, and Uribe (2010); Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramirez, and Uribe (2011); Chang and Fernández (2013); Fernández and Gulan (2015)) or both (Miyamoto and Nguyen (2017)).[1]

While most earlier studies have been silent about labor market dynamics in developing economies, Boz, Durdu, and Li (2015) recently show that the business cycle properties of key labor market variables (i.e., real earnings, employment, and hours worked) in developing economies are also different from those in developed economies. By expanding the sample economies studied in Neumeyer and Perri (2005), Boz, Durdu, and Li (2015) confirm the finding from Neumeyer and Perri (2005) that the relative variability of hours worked and employment to output in developing economies is lower than that in developed economies, despite the higher relative variability of consumption and real wages to output in the former group. Moreover, in the independent stream of research, Bick, Fuchs-Schündeln, and Lagakos (2018) document that average hours worked per adult is substantially higher in low-income countries than in high-income countries, suggesting that not only business cycle properties, but also are the steady-state characteristics of labor markets different between the two groups.

These stylized facts suggest that widely used GHH preferences by Greenwood, Hercowitz, and Huffman (1988) in the small open economy literature since Mendoza (1991) meets its limitation when it comes to understanding the labor market fluctuations in developing economies. GHH preferences have been adopted in many small open economy models (Correia, Neves, and Rebelo

[1] Throughout the paper, we use term "developing economies" to denote non-advanced economies, including both emerging market economies and developing economies under the IMF definition.

(1995), Neumeyer and Perri (2005), and Garcia-Cicco, Pancrazi, and Uribe (2010), among others) to generate countercyclical behaviors of the trade balance-to-output and avoid the case where hours worked declines in response to a rise in productivity due to the wealth effect. However, the marginal rate of substitution between consumption and leisure is independent of the consumption decision with this type of preferences. Thus, it eliminates the wealth effect, and labor supply decisions become independent from intertemporal considerations. Since labor supply is fully responsive to the current shocks there is less room for the wage to adjust, which contradicts to large volatility of real wages in developing economies.

Taken together, these findings suggest that accounting for the distinct feature of labor market dynamics in developing economies is crucial for understanding their business cycle properties. Nevertheless, an analysis on labor market dynamics in developing economies has been largely overlooked. For example, while a bulk of the theoretical and empirical studies has focused on the response of hours worked to technology shocks in advanced economies— especially the U.S. (Galí (1999); Christiano, Eichenbaum, and Vigfusson (2004); Francis and Ramey (2005); Basu, Fernald, and Kimball (2006)) or the G7 economies (Galí (2004); Dupaigne and Fève (2009))—, there has been no counterpart study for developing economies to the best of our knowledge.

We fill this gap in the literature by examining the responses of hours worked and employment to technology shocks using a large international panel data, including many developing economies, over the last 45 years. Our contribution to the literature is threefold. First, we find robust evidence that the responses are qualitatively different between the two groups of countries using a structral Vector Autoregression (VAR) model with long-run restrictions, *à* la Blanchard and Quah (1989) and Galí (1999). The response of hours worked and employment to the identified technology shock is smaller in developing economies than advanced economies. Second, we document a strong correlation between the level of income per capita (our proxy for subsistence consumption) and the business cycle properties regarding consumption and labor variables. Interestingly, other potential characteristics, such as openness and labor market regulations, fail to explain the cross-country hetereogeneity in the business cycle properties. Lastly, we build a simple real business cycle (RBC) model augmented with subsistence consumption to explain the set of novel empirical findings.

The growth/development literature has proven that a growth model augmented with subsistence consumption explains the differences in growth experience across countries (Steger (2000); Ravn, Schmitt-Grohe, and Uribe (2008); Achury, Hubar, and Koulovatianos (2012); Herrendorf, Rogerson, and Valentinyi (2014)). To the extent to which subsistence consumption is more important (i.e., binding) in developing countries than developed ones, it becomes a promising candidate to explain the differences in business cycle properties. To the best of our knowledge, however, subsistence consumption has not been used to explain a distinct feature of developing economy business cycles.

We find that the equilibrium properties of our model are consistent with the observed dynamics in developing economies. As the subsistence level of consumption increases—the model economy becomes resembling less-developed countries—, the response of hours worked to the positive technology shock becomes smaller, which is consistent with our empirical finding. We further show that the model-implied business cycle properties, including the larger volatility of wage and consumption relative to output and the smaller volatility of hours worked relative to output, are also consistent with the data. Moreover, the recent observation that workers work more in low-income countries (Bick, Fuchs-Schündeln, and Lagakos (2018)) is also obtained as an equilibrium outcome.

Economic intuition behind the success of our model is simple. The inclusion of subsistence consumption strengthens the income effect in developing economies. As the income effect becomes stronger, the effective slope of the labor supply curve becomes steeper. As a result, with the technology shock of the same magnitude shifting out the labor demand curve, hours worked responds less in the economy with a high level of subsistence consumption. Moreover, workers must supply a high level of labor at the steady state to maintain their consumption above the subsistence level. Thus, on the one hand, workers cannot supply more labor in response to a positive technology shock, as marginal disutility from working is too high. On the other hand, workers cannot reduce labor supply in response to a negative technology shock because of the binding subsistence consumption constraint. The smaller response of hours worked implies that hours worked becomes less volatile but real wage becomes more volatile. As a result, the response of consumption to the technology shock becomes larger compared to the model without subsistence consumption to hold the labor market equilibrium condition.

The rest of the paper is organized as follows. We first introduce data used for our empirical analysis in Section 2 and then conduct an extensive empirical analysis based on structural VAR models in Section 3. Section 4 introduces our RBC model with subsistence consumption and demonstrates its empirical relevance. In Section B, we further discuss if existing theories can explain our findings. Section 5 concludes.

2 Data

We use 45 years of annual data on labor productivity, total hours worked, and employment for the sample period between 1970 and 2014 in our baseline empirical analysis. While using higher frequency data is ideal to discover underlying labor market dynamics at a business cycle frequency, it reduces both the cross-sectional and time-series coverage of the data substantially, especially for developing economies. It is still the case that quarterly data on hours worked are largely limited to advanced economies. For example, Ohanian and Raffo (2012) construct quarterly hours worked data over the last 50 years, but only for 14 OECD countries.[2]

Labor productivity is defined as (i) output per hours worked (the ratio of real output to total hours worked) and (ii) output per employed person (the ratio of real output to person employed). We take most of the data from the widely-used Conference Board Total Economy Database and the Penn World Table 9.0, which provide extensive historical data on GDP, hours worked, employment, consumption, and population for both advanced and developing economies. Hours worked data from the Conference Board are adjusted to reflect most sources of cross-country variation in hours worked, including contracted length of the work week, statutory holidays,

[2] In the previous version of the paper, we conduct a similar analysis using quarterly data on employment from 28 advanced and 29 developing economies since 1980 and find an even starker difference in the responses of employment to the permanent technology shock between the two groups. While this result is available upon request, we choose annual hours worked data instead of quarterly employment data in the baseline analysis to capture the both the intensive and extensive margin of labor and be consistent with earlier structural VAR analyses on advanced economies, such as Christiano, Eichenbaum, and Vigfusson (2004), Galí (2004), and Basu, Fernald, and Kimball (2006).

paid vacation and sick days, and days lost due to strikes, and are consistent with NIPA measures of output.[3]

While the time-series coverage for developed economies often goes back to the 1950s, the coverage for developing economies is typically shorter. To balance between the time-series dimension and cross-sectional dimension of our analysis, we use the data from 1970 whereby labor productivity measured by hours worked is available in 43 countries (27 advanced and 16 developing countries) and labor productivity measured by employment is available in 103 countries (31 advanced and 72 developing countries). Output is converted to 2016 price level with updated 2011 PPPs, which allows for the aggregation across countries in a consistent manner. Since our baseline measure of productivity requires the aggregation of output and labor across countries, our sample should be fully balanced.

Table 2.1 presents the list of countries used in the baseline analysis using hours worked data and their business cycle properties, including the relative variability of hours worked, employment, and consumption to output and their unconditional correlation with output.[4] Table AA.1 in the appendix presents the full list of countries used in the robustness check using employment data.[5] Compared to advanced economies, developing economies are characterized by smaller relative variability of both hours worked and employment to output, which corroborates the empirical stylized fact in Neumeyer and Perri (2005) and Boz, Durdu, and Li (2015) by employing a substantially larger sample.[6]

[3] See The Total Economy Database for further details.

[4] We do not report other business cycle properties here. See Boz, Durdu, and Li (2015) and Miyamoto and Nguyen (2017) for the updated statistics.

[5] All of our empirical results hardly change when we regroup some advanced economies into a developing economy category. For example, some of east Asian industrial countries are now considered as advanced economies, while their income status in the earlier period is clearly at the developing economy level. We test the robustness of our findings by relabeling six advanced economies (Czech Republic, Israel, Hong Kong, Singapore, South Korea, and Taiwan) as developing economies.

[6] One might argue that the low variability of hours worked and employment in developing economies is driven by a large public sector in these countries. However, Boz, Durdu, and Li (2015) provide some empirical evidence that the public sector in these countries is characterized by higher volatility of hours worked than the private sector.

Table 2.1: Countries used in the baseline analysis and their business cycle properties

Country	$\sigma(h)/\sigma(y)$	$\sigma(n)/\sigma(y)$	$\sigma(c)/\sigma(y)$	$\rho(h,y)$	$\rho(n,y)$	$\rho(c,y)$
			Advanced economies			
Australia	0.94	0.80	0.73	0.68	0.64	0.41
Austria	0.93	0.38	0.85	0.57	0.46	0.72
Belgium	0.82	0.50	0.81	0.35	0.42	0.62
Canada	0.92	0.76	0.69	0.78	0.77	0.73
Denmark	0.90	0.64	0.92	0.59	0.72	0.71
Finland	0.69	0.69	0.70	0.77	0.73	0.81
France	0.82	0.47	0.81	0.43	0.70	0.75
Germany	0.66	0.46	0.78	0.51	0.31	0.44
Greece	0.55	0.53	0.93	0.54	0.58	0.86
Hong Kong	0.59	0.49	0.99	0.44	0.53	0.75
Iceland	0.74	0.63	1.33	0.61	0.69	0.84
Ireland	0.91	0.84	0.89	0.69	0.72	0.75
Italy	0.60	0.47	0.97	0.51	0.51	0.76
Japan	0.49	0.30	0.80	0.74	0.66	0.84
Luxembourg	0.59	0.46	0.46	0.46	0.38	0.36
Netherlands	0.82	0.67	0.93	0.48	0.64	0.75
New Zealand	0.90	0.81	0.90	0.47	0.39	0.68
Norway	0.90	0.81	0.91	0.27	0.42	0.64
Portugal	0.69	0.64	1.02	0.33	0.33	0.70
Singapore	0.83	0.78	0.82	0.55	0.46	0.66
South Korea	0.90	0.52	0.93	0.67	0.75	0.83
Spain	1.19	1.09	0.99	0.69	0.71	0.92
Sweden	0.77	0.75	0.63	0.69	0.59	0.57
Switzerland	0.76	0.66	0.58	0.71	0.71	0.69
Taiwan	0.56	0.42	0.90	0.73	0.71	0.71
United Kingdom	0.94	0.66	0.95	0.67	0.62	0.84
United States	0.98	0.70	0.70	0.85	0.81	0.85
Median	0.82	0.64	0.89	0.59	0.64	0.73
Mean	0.79	0.63	0.85	0.58	0.59	0.71
			Developing economies			
Argentina	0.59	0.44	1.14	0.74	0.68	0.87
Bangladesh*	0.57	0.55	1.37	0.53	0.51	0.46
Brazil	0.67	0.69	1.20	0.31	0.30	0.76
Chile	0.56	0.53	1.18	0.57	0.63	0.84
Colombia	0.90	0.93	1.05	0.28	0.26	0.87
Indonesia	0.60	0.55	0.92	0.19	-0.02	0.62
Malaysia	0.48	0.49	1.34	0.42	0.39	0.70
Mexico	0.59	0.58	1.05	0.70	0.70	0.93
Pakistan	0.89	0.88	1.35	-0.04	-0.07	0.42
Peru	0.41	0.31	1.09	0.19	0.20	0.86
Philippines	0.66	0.64	0.53	0.02	0.02	0.82
Sri Lanka	0.80	0.63	1.12	0.09	0.11	0.24
Thailand	1.25	0.64	1.55	0.30	0.53	0.52
Turkey	0.49	0.49	1.16	-0.10	-0.04	0.63
Venezuela	0.52	0.42	1.31	0.38	0.17	0.68
Vietnam*	0.72	0.27	0.79	-0.02	-0.15	0.47
Median	0.60	0.55	1.15	0.29	0.23	0.69
Mean	0.67	0.57	1.13	0.29	0.26	0.67

Note: σ denotes the standard deviation of the variable and ρ denotes the correlation between the variables. h, n, c, and y denote hours worked, employment, consumption, and output, respectively. * denotes a country belonging to the low-income category.

3 Empirical analysis

The stylized facts about the business cycle properties of developing economies documented in the previous section suggest that some frictions in their labor markets prevent adjusting labor input to exogenous shocks. Among candidates of business cycle drivers, we focus on the behavior of labor market variables in response to a permanent technology shock and leave a non-technology shock unidentified among potential sources, such as shocks to a preference, government spending, and monetary policy for the sake of the parsimony of the model. Following much of the earlier literature, we apply a structural VAR model with Blanchard and Quah (1989)'s long-run restrictions—*à* la Galí (1999)—to a large international panel dataset covering both advanced and developing economies.

Unlike Galí (1999) who study the response of hours worked and employment to a permanent technology shock in the U.S. economy, our international setup poses some challenges on how to define a technology shock in the structural VAR model. One might simply define a country-specific technology or productivity shock by dividing real output of each economy by total hours worked as in Galí (1999). However, to the extent that technology shocks spill over from one country to others, this naive approach could result in severe bias in the measurement of a technology shock. For example, Kose, Prasad, and Terrones (2003), Kose, Otrok, and Whiteman (2003), and Stock and Watson (2005) find a large contribution of world common shocks to macroeconomic variables in individual countries by estimating a factor model.[7] Recently, Miyamoto and Nguyen (2017) estimate a small open economy RBC model with financial frictions and common shocks using 100 years of data for both advanced and developing economies. They find that world common shocks contribute to a substantially large fraction of fluctuations in these countries and perhaps more interestingly, common shocks are of similar importance for both groups of countries, suggesting that the importance of world common shocks is not limited to developed economies.

[7] Rabanal, Rubio-Ramirez, and Tuesta (2011) also provide evidence that TFP processes for the U.S. and the "rest of the world" are characterized by a vector error correction model (VECM) and that adding cointegrated technology shocks to the standard international RBC model helps explain the observed high real exchange rate volatility.

To resolve this issue, we adopt an approach by Dupaigne and Fève (2009) in estimating the response of labor input to a technology shock in the international context. Based on the existing evidence on a common process in technology shocks across countries, Dupaigne and Fève (2009) claim that the international transmission of shocks prevents the direct application of Galí (1999)'s model to the international data because foreign non-permanent shocks, on top of domestic ones, contaminate the permanent technology shock identified from a country-level structural VAR model. Instead, Dupaigne and Fève (2009) propose an alternative structural VAR specification that includes an aggregate measure of world labor productivity.[8] The aggregation across countries offsets the country-level stationary shocks which contaminate country-level data, thus mitigates the identification problem.

To be more specific, Dupaigne and Fève (2009) replicate Galí (1999)'s estimation of the short-run response of labor input to a permanent technology shock using actual data on the G7 countries from 1978 to 2003. When estimated with country-level quarterly data on the growth rate of labor productivity and per-capita employment, the structural VAR model reveals a negative response of employment on impact in most of the G7 countries. However, the same experiment with the G7 aggregate data, in which both real output and employment are aggregated over the seven countries, results in an increase in employment, suggesting that labor productivity of G7 countries cointegrates and displays a single stochastic trend.

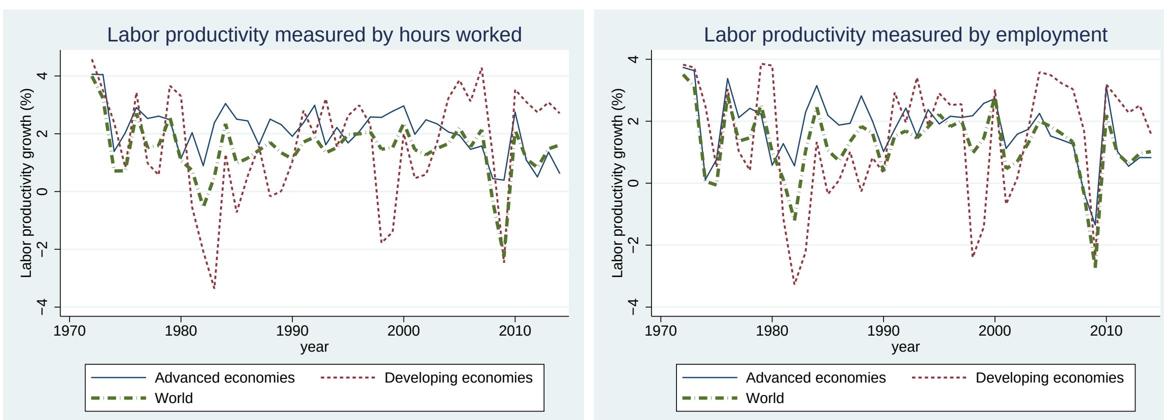
Based on the estimation of the data generated by the structural model, Dupaigne and Fève (2009) argue that a measure of labor productivity aggregated across countries improves the identification of the response of the labor input to a technology shock in the international context. Moreover, the contamination of country-level labor productivity by country-specific stationary shocks has two quantitative implications highly relevant for our purpose: (i) the smaller the country, the larger the downward bias should be and (ii) the bias is minimized for the widest aggregation available. Considering the typical size of each developing economy, the aggregation gives developing economies the best chance to have a larger response of labor input to the permanent technology shock. Moreover, 44 countries in our baseline sample accounts for the

[8]This strategy is also related to the other efforts to identify permanent technology changes by aggregation, such as Chang and Hong (2006).

bulk of world output.

Following Galí (1999), we consider a VAR model on the growth rate of average labor productivity (APL) Δz_t^h and hours worked Δh_t (and also employment Δn_t for a robustness check) to evaluate the response of labor input to permanent technology shocks. Following Dupaigne and Fève (2009) Galí (1999), we define labor productivity as the ratio of real output aggregated over the countries in the sample to total hours worked that is also aggregated over the same sample. Figure 3.1 shows so-called the "world labor productivity" in this manner using hours worked (left panel) and employment (right panel) from 1970 to 2014. We also compute group-specific labor productivity that is aggregated only over the countries belonging to the same income group. Overall, the pattern of labor productivity fluctuations does not depend much on however it is measured.

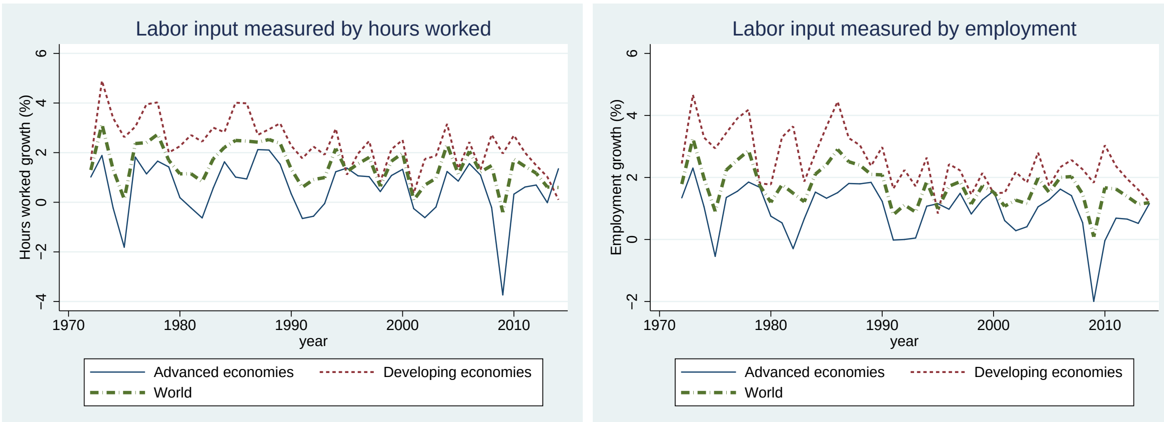
Figure 3.1: Labor productivity: hours worked vs. employment



Note: This figure displays the labor productivity measured by hours worked (left panel) and employment (right panel) for advanced economies, developing economies, and the world economy.

Figure 3.2 aplots the fluctuations in aggregated labor input measured by hours worked (left panel) and employment (right panel) for the same period. It is apparent that variability in labor input is smaller in a sample of developing economies than advanced economies even when it is aggregated within each group.

Figure 3.2: Labor input: hours worked vs. employment



Note: This figure displays the labor input measured by hours worked (left panel) and employment (right panel) for advanced economies, developing economies, and the world economy.

3.1 Identification of technology shocks

We estimate the following bivariate VAR model:

$$Y_t = \sum_{j=1}^{p} B_j Y_{t-j} + u_t, \tag{3.1}$$

where $Y_t = (\Delta z_t^h, \Delta h_t)'$ and $u_t = (u_{1,t}, u_{2,t})'$ with $E[u_t u_t^{'}] = \Sigma$. The number of lags p is selected using standard information criteria, such as Akaike Information Criterion. Under usual conditions, this VAR model admits a VMA(∞) representation $Y_t = C(L)u_t$, where $C(L) = (I_2 - B_1 L - ... - B_p L_p)^{-1}$ and L is a lagged operator. The structural representation of this VMA(∞) results in

$$Y_t = A(L)e_t, \tag{3.2}$$

where $e_t = (e_t^z, e_t^m)'$. e_t^z denotes the technology shock, while e_t^m denotes the non-technology shock. The identifying restriction of Galí (1999) assumes that the non-technology shock does not have a long-run effect on labor productivity, which implies that the upper triangular element of $A(L)$ in the long run must be zero, i.e., $A_{12}(1) = 0$. In order to uncover the identifying restriction from the estimated VAR model, the matrix $A(1)$ is computed as the Choleski decomposition of

$C(1)\Sigma C(1)'$. The structural shocks e_t can then be recovered, using $e_t = A(1)^{-1}C(1)u_t$.

In this VAR model, it is crucial to choose an appropriate specification (levels vs first-differences) of labor input (Christiano, Eichenbaum, and Vigfusson (2004)). Thus, we perform the Augmented Dickey Fuller (ADF) test for unit root in labor input. For each group of economies, we regress the growth rate of aggregate employment on a constant, its lagged levels, and the lags of its first differences. The results of the ADF test with two lags (including a time trend) are displayed in Table 3.1. Similar to the aggregation over the G7 countries in Dupaigne and Fève (2009), the null hypothesis of unit root cannot be rejected at conventional levels for the level of hours worked and employment in all aggregation, whereas it is clearly rejected for the first-differences at least at the 5% level, giving support to the first-differences specification.[9]

Table 3.1: ADF unit root test on aggregated hours worked and employment

	Log-level	Critical values			Difference	Critical values		
		1%	5%	10%		1%	5%	10%
Hours worked								
World	-0.785	-4.224	-3.532	-3.199	-4.206	-4.224	-3.532	-3.199
Advanced	-1.749	-4.224	-3.532	-3.199	-4.540	-4.224	-3.532	-3.199
Developing	-1.419	-4.224	-3.532	-3.199	-3.914	-4.224	-3.532	-3.199
Employment								
World	-1.538	-4.224	-3.532	-3.199	-4.176	-4.224	-3.532	-3.199
Advanced	-1.520	-4.224	-3.532	-3.199	-4.330	-4.224	-3.532	-3.199
Developing	-2.272	-4.224	-3.532	-3.199	-3.732	-4.224	-3.532	-3.199

Note: ADF t-statistics for the null hypothesis of a unit root in the log-level or growth rate of each time series, based on the ADF test with two lags, an intercept (and a time trend for log-level data). Sample period 1970-2014.

3.2 Baseline results

We first report the baseline results using the aggregate measure of technology shocks and the aggregated labor input as suggested by Dupaigne and Fève (2009). Here, the world labor productivity is defined as the ratio of the world output using the PPP-adjusted real GDP to the sum of hours worked over 43 countries in the sample where hours worked data are available since

[9] For a country-by-country case in the robustness check section, we also conduct the ADF test for labor input in each individual countries. In most countries, we find that the null hypothesis of unit root cannot be rejected for the level of hours worked and employment, lending support to the first-differences specification.

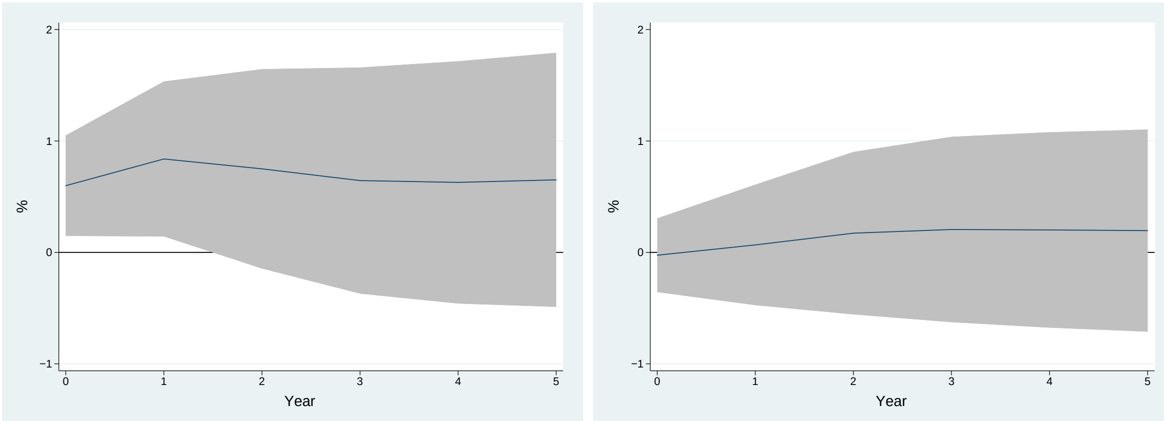
1970. In this exercise, hours worked is aggregated over a balanced panel of 27 advanced and 16 developing economies, respectively. We use the PPP-adjusted GDP to take into account for differences in purchasing power across countries, which better approximates standard of living in each country.

Figure 3.3 displays the estimated responses of aggregated hours worked to the world permanent productivity shock. The left panel reports the impulse response function (IRF) of hours worked in the advanced economy group and the right panel shows the IRF of hours worked in the developing economy group to the one standard deviation shock to the same world productivity process, respectively. 90% confidence interval is obtained by standard bootstrap techniques, using 500 draws from the sample residuals. On the one hand, hours worked increases significantly following the world technology shock in the advanced economy group, which is consistent with the standard prediction of RBC models. As argued by Dupaigne and Fève (2009), aggregating productivity over countries resolves the technology-hours worked puzzle raised by Galí (1999). On the other hand, hours worked does not respond to the world technology shock in the developing economy group, suggesting that labor market dynamics in response to the technology shock in these countries differ sharply from advanced economies. While the point estimates are essentially zero over the five-year horizon, the confidence interval of estimates is narrower than the advanced economy group, suggesting that the result is not driven by imprecise estimates.

We have assumed that both groups of advanced and developing economies are subject to the identical world productivity process. To the extent to which each individual economy is fully integrated to the rest of the world, it is a reasonable assumption on the productivity process. However, our analysis contains a sample of developing economies where the integration with the rest of the world is arguably weaker. For example, Kose, Prasad, and Terrones (2003) argue that enhanced global spillovers of macroeconomic fluctuations due to trade and financial integration is mostly limited to advanced countries. Using a dynamic factor model applied to a large number of countries, Kose, Otrok, and Whiteman (2003) also find investment dynamics are much more idiosyncratic in developing countries than in developed ones.

Thus, we also use a group-specific measure of labor productivity by using the ratio of the real

Figure 3.3: IRF of hours worked to the world permanent technology shock



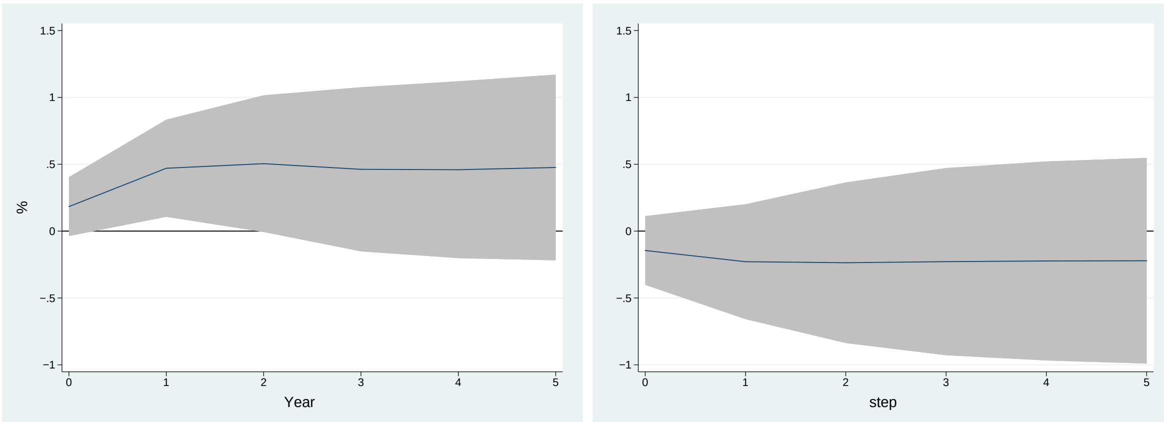
Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model of advanced economies $(\Delta z_t^{World,h}, \Delta h_t^{Advanced})$ in the left panel and developing economies $(\Delta z_t^{World,h}, \Delta h_t^{Developing})$ in the right panel and its 90% confidence interval from 500 bootstraps.

output aggregated over each group to hours worked aggregated over the corresponding group, under the working assumption that technology spillover occurs mainly among countries with a similar income-level. Figure 3.4 displays the results using the group-specific technology shocks, suggesting that the smaller response of hours worked to the permanent technology shock in developing economies is not simply driven by the fact that the technology level of these countries is distant from the world technology frontier, such as the U.S.

Then, we repeat our analysis using an alternative measure of labor input (employment) and labor productivity. In this case, we define the world labor productivity as the ratio of the real output of the world using the PPP-adjusted real GDP to the sum of total employment of the same 43 countries. When we estimate equation 3.1, Y_t becomes $(\Delta z_t^n, \Delta n_t)'$, where Δn_t is the growth rate of total employment. Again, Figure 3.5 confirms that the significant response of labor input to the positive permanent technology shock—as predicted by a class of standard RBC models—is only present in a group of advanced economies and this finding hardly changes when using the group-specific technology shock (Figure A.1 in the appendix).[10]

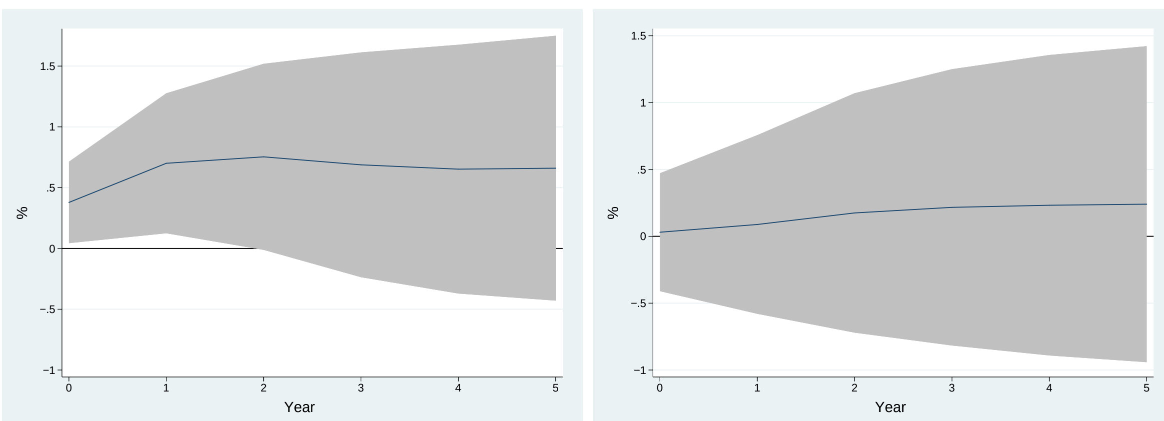
[10]Dropping the post-Global Financial Crisis period (from 2008) hardly affects the difference in the response of hours worked and employment to the world technology shock.

Figure 3.4: IRF of hours worked to the group-specific permanent technology shock



Note: This figure displays the impulse response function of hours worked to the permanent group-specific technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{Advanced,h}, \Delta h_t^{Advanced}$) in the left panel and developing economies ($\Delta z_t^{Developing,h}, \Delta h_t^{Developing}$) in the right panel and its 90% confidence interval from 500 bootstraps.

Figure 3.5: IRF of total employment to the world permanent technology shock



Note: This figure displays the impulse response function of total employment to the permanent world technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{World,n}, \Delta n_t^{Advanced}$) in the left panel and developing economies ($\Delta z_t^{World,h}, \Delta n_t^{Developing}$) in the right panel and its 90% confidence interval from 500 bootstraps.

3.3 Robustness checks

Our sample of developing countries also includes low-income countries (LICs) where the quality of economic data might be questionable. Presumably larger measurement errors in these countries might have biased the response of labor input to the permanent technology shock towards zero in the developing economy group. Thus, we repeat our analysis after dropping a set of low-income countries. The left panel in Figure A.2 in the appendix shows that our findings are not driven by the inclusion of LICs. Another concern regarding a group-specific technology shock is that technology shocks from advanced economies might be more important than their own technology shocks for developing economy business cycles. We repeat our analysis for a group of developing economies using so called the "advanced economy technology shock." Since this modification affects only the exercise of developing countries, we do not report the results on advanced economies. The right panel in Figure A.2 in the appendix confirms that the alternative measure of the technology process does not alter our conclusion.

In addition to trade globalization that started from the earlier decades, the wave of financial globalization since the mid-1980s has been marked by a surge in capital flows between advanced and developing countries (for example, Prasad, Rogoff, Wei, and Kose (2007)). In this regard, our analysis using the aggregate measure of technology shocks may not capture the pattern of technology spillover during the pre-financial globalization era, resulting in biased estimates for the group of developing economies, in particular. Perhaps, our aggregation across countries makes more sense for the recent period with a significant trade and financial integration of the world economy. Thus, we repeat our analysis using the sample from 1985 only. Figure A.3 in the appendix shows that the responses of hours worked still differ between the two groups. Together with the robustness check using the developing economy-specific technology shock in the previous section, this finding suggests that the limited technology spillovers from advanced to developing economies are unlikely the reason of the muted response of labor input in developing economies.[11]

We have used only 43 countries throughout the analysis since enough time-series data on hours worked are only available in these countries. However, the analysis of the 43 countries does not necessarily span the whole part of the world economy, resulting in potential bias in the measured world productivity. Data on total employment, however, are available in a large

[11] We also conduct the same set of robustness checks using total employment as a labor input and find similar results.

number of countries, especially in developing economies (31 advanced economies and 72 developing economies). As shown in Figure A.4 in the appendix, both the qualitative and quantitative differences between advanced and developing economies regarding the response of employment to the permanent world technology shock using a substantially larger sample of 103 countries resemble the baseline results.[12]

3.4 Additional VAR exercises

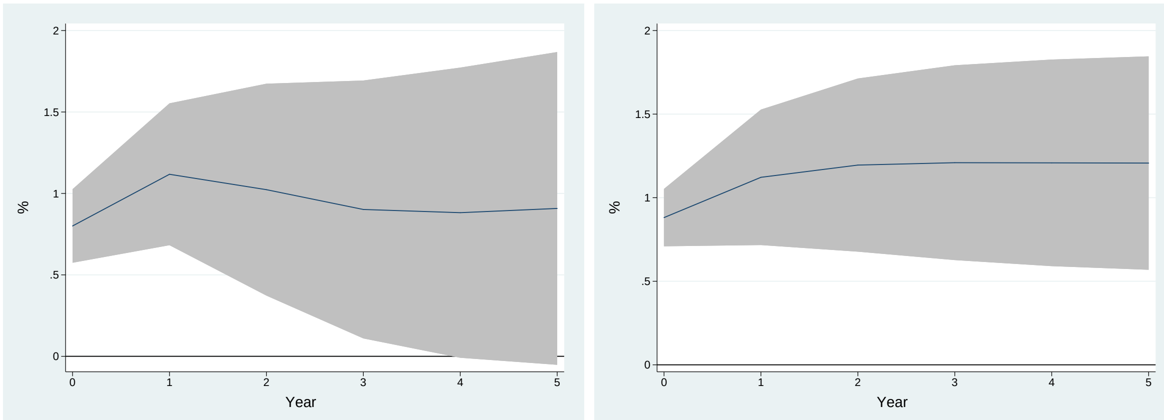
Response of hours worked to the non-technology shock. So far, we have only focused on the response of hours worked (or employment) to the technology shock identified from long-run restrictions. However, testing whether the response of labor input to the non-technology shock differs between advanced and developing economies helps us understand a source of different properties of labor market dynamics. We estimate the response of labor input at the group level to the non-technology shock, which includes all kind of disturbances that do not have a long-run effect on world labor productivity.

Figure 3.6 plots the response of hours worked to the non-technology shock, which is constructed from the baseline VAR model used in Figure 3.3. Interestingly, the responses of hours worked to the non-technology shock are remarkably similar between the two groups of countries, suggesting that the conditional response to the technology shock plays an important role in understanding the distinct feature of labor market dynamics in developing economies from that in advanced economies. This similar pattern is robust to (i) using a group-specific productivity shock and (ii) using employment instead of hours worked in the VAR model.

Another metric to evaluate the importance of the technology shock in explaining fluctuations in labor input is forecast error variance decomposition. Table 3.2 summarizes the share of variance in labor input explained by the technology shock in advanced and developing economies, respectively. It is clear that the technology shock is an important driver of dynamics of hours worked and employment in advanced economies, while labor market dynamics in developing economies are dominantly driven by the non-technology shock. Together with evidence from

[12] Our results also hold when using a smaller sample of emerging market economies (47 countries) after dropping low-income countries, which might be subject to the data quality concern.

Figure 3.6: IRF of hours worked to the world non-technology shock



Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model of advanced economies in the left panel and developing economies and its 90% confidence interval from 500 bootstraps.

Figure 3.6, Table 3.2 suggests that understanding the muted response of labor input to the technology shock in developing economies is key to understanding their distinct business cycle properties from advanced economies.

Table 3.2: Share of variation in labor input explained by the technology shock (%)

	Advanced economies			Developing economies		
Horizon	Baseline	Group technology	Employment	Baseline	Group technology	Employment
1	56.16	27.24	65.88	0.42	0.89	0.03
2	56.22	35.66	72.41	1.95	1.37	0.43
3	56.37	34.92	72.09	3.36	1.36	1.30
4	56.52	35.03	72.16	3.49	1.37	1.49
5	56.52	35.02	72.21	3.50	1.37	1.51

Note: Because there are only two structural shocks, the non-technology shock accounts for the rest of the variation. "Baseline" indicates the forecast error variance decomposition from the baseline specification. "Group technology" indicates the forecast error variance decomposition from the specification using the group-specific technology shock. "Employment" indicates the forecast error variance decomposition from the specification using employment instead of hours worked.

Response of real consumption to the technology shock. We have worked with a parsimonious bivariate VAR model including only labor productivity and labor input variables to study potential heterogeneity in the response of hours worked and employment to the technology shock given our primary focus on understanding distinguished labor market dynamics in developing economies from those in advanced economies. Nevertheless, any sensible economic mechanism must explain simultaneously another key feature of business cycle properties in developing economies—the higher variability of consumption to output. To shed some light on this issue, we also estimate a trivariate VAR model augmented with real consumption at the group level as a third variable in the VAR system.

In other words, we replace $Y_t = (\Delta z_t^h, \Delta h_t)'$ in equation 3.1 with $Y_t = (\Delta z_t^h, \Delta h_t, \Delta c_t)'$, where Δc_t is the annual growth in real consumption aggregated at the group level. We aggregate real consumption across countries in each group similarly to the construction of aggregated real output in the previous section. We assume that the upper triangular element of $A(L)$ in the long run must be zero by setting $A_{12}(1) = A_{13}(1) = A_{23}(1) = 0$.[13]

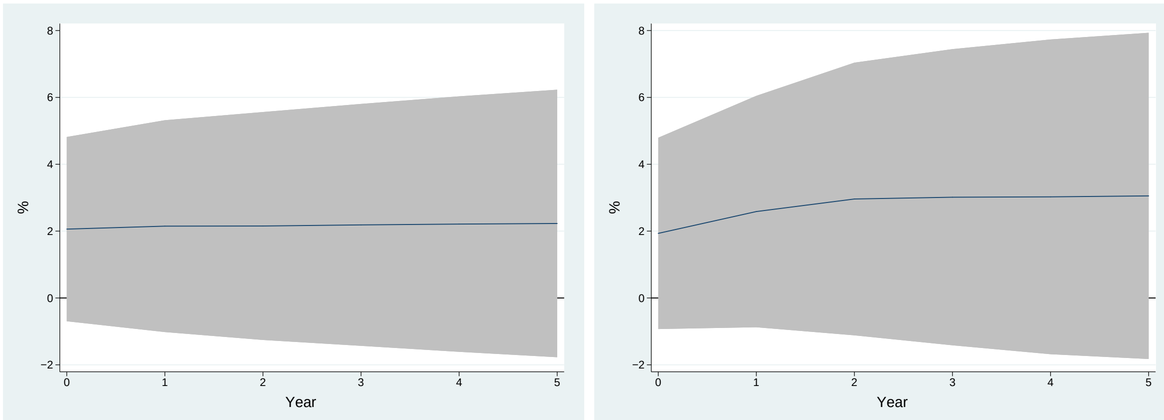
Figure 3.7 compares the response of consumption to the world technology shock between advanced and developing economies. Unlike the response of labor input, the magnitude of the consumption response in developing economies is no smaller than that in advanced economies, despite the wide confidence interval in both cases. Moreover, the large response of consumption to the technology shock in developing economies mitigates concerns that the muted response of hours worked and employment is driven by measurement errors the data from developing economies.

3.5 Country-by-country analysis

The response of labor input analyzed in the previous section uses aggregate-level labor input from each group. Following Dupaigne and Fève (2009), we also test the robustness of our findings by using country-level labor input instead. In other words, for each country i, $Y_{i,t}$ is defined as $(\Delta z_t^{World,h}, \Delta h_{i,t})'$. For each group of countries in the main sample, we compute the interquartile range of point estimates to summarize the results. Figure 3.8 shows the case of hours worked and Figure 3.9 shows the case of employment. In both cases, it is clear that the response of labor

[13] As long as we are interested in the response of hours worked and consumption to the technology shock, we are not particularly concerned about the long-run restriction imposed on the structural relationship between hours worked and consumption (i.e., $A_{23}(1)$). Our results still hold when we reverse the ordering between hours worked and consumption in the VAR model above keeping the same long-run restrictions.

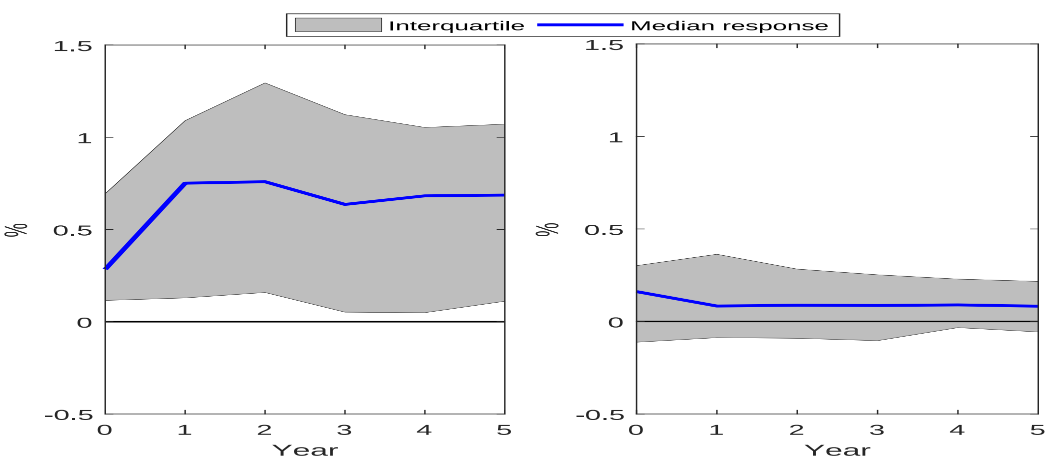
Figure 3.7: IRF of consumption to the world technology shock



Note: This figure displays the impulse response function of consumption to the permanent world technology shock in a trivariate VAR model of advanced economies in the left panel and developing economies and its 90% confidence interval from 500 bootstraps.

input is much larger in advanced economies compared to developing economies, confirming the results using aggregate-level labor input.[14]

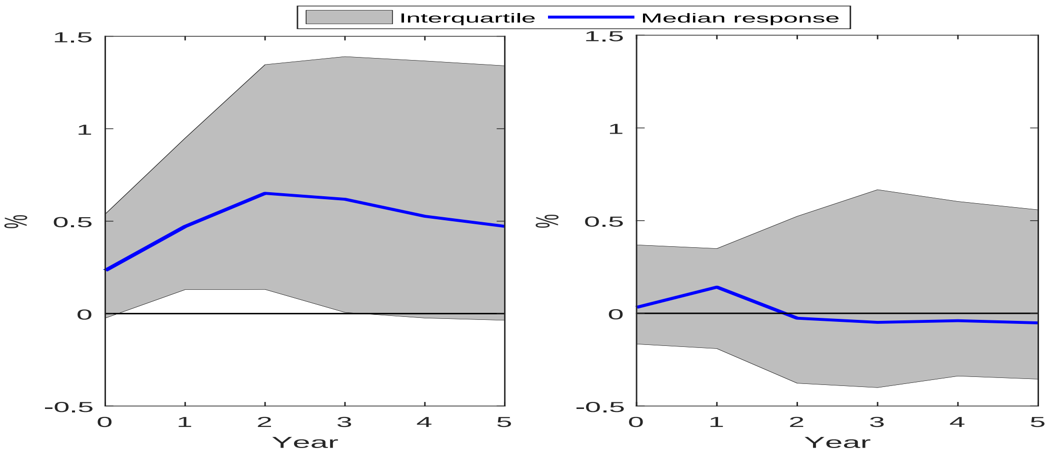
Figure 3.8: Country-by-country IRF of hours worked to the world permanent technology shock



Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model $(\Delta z_t^{World,h}, \Delta h_{i,t})$. The left panel shows the interquartile distribution of advanced economies and the right panel shows the interquartile distribution of developing economies.

[14]The pattern of the response of employment hardly changes when extending the sample to include all 103 countries. The results are available upon request.

Figure 3.9: Country-by-country IRF of employment to the world permanent technology shock

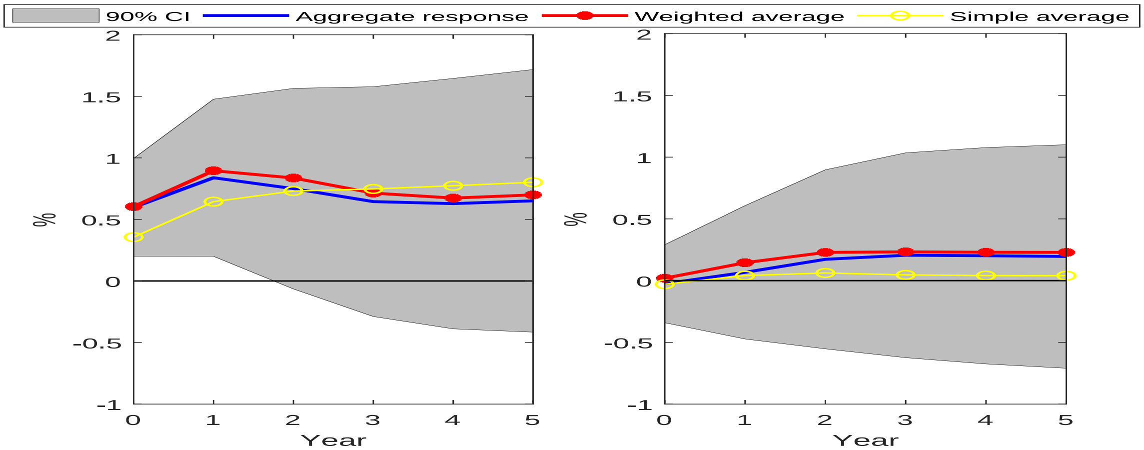


Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model $(\Delta z_t^{World,n}, \Delta n_{i,t})$. The left panel shows the interquartile distribution of advanced economies and the right panel shows the interquartile distribution of developing economies.

Dupaigne and Fève (2009) show that the weighted average of the IRFs from each of the G7 economies using the country-level labor input is remarkably similar to the IRFs from the baseline analysis using the aggregate-level labor input, highlighting the success of their identification scheme. We also compute the weighted average of the IRFs from each group using the PPP-adjusted GDP in 2000 as a weight. Figure 3.10 compares this weighted response using country-level labor input with the previous response using aggregate-level labor input. We also find that the responses are remarkably similar, lending further support to the baseline results. However, the simple (unweighted) average yields some discrepancy because it is not consistent with the way we calculate aggregate-level labor input and labor productivity.

As a final robustness check, we include the difference between the country-level labor productivity and the aggregate labor productivity $(\Delta z_{i,t}^h - \Delta z_t^{World,h})$ as an additional variable. To the extent to which a single stochastic trend hits the country-level labor productivity permanently, the labor productivity differentials help capture persistent country-specific components in labor productivity. As shown in Figure A.5, the response of hours worked in the trivariate VAR model is similar to those obtained with the bivariate VAR model. If anything, the addition

Figure 3.10: Average IRF of hours worked to the world permanent technology shock



Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model $(\Delta z_t^{World,h}, \Delta h_{i,t})$. The left panel shows the average of the country-by-country responses of advanced economies and the right panel shows the average of the country-by-country responses of developing economies.

of productivity differentials in the VAR slightly shifts down the responses of labor input for both groups.

4 RBC model augmented with subsistence consumption

We have established robust stylized facts about the response of hours worked and employment to the permanent technology shock. Combined with the distinct business cycle properties regarding developing economy labor markets (Li (2011) and Boz, Durdu, and Li (2015)) and higher steady-state hours worked in these economies (Bick, Fuchs-Schündeln, and Lagakos (2018)), our new findings provide challenges to the existing business cycle models of developing economies. A broad class of RBC models—regardless of a closed economy or a small open economy—is known to perform poorly in explaining labor market variables because RBC models mostly depend on changes in labor demand through productivity shocks to affect employment. While the common use of GHH preferences adopted in many small open economy models as an attempt to explain the distinct consumption dynamics in these economies (Mendoza (1991), Correia, Neves, and Rebelo (1995), Neumeyer and Perri (2005), and Garcia-Cicco, Pancrazi, and Uribe (2010), among others) further exacerbates the performance of the RBC models in the labor market dimension, the muted response of hours worked and employment to the positive technology shock in our structural VAR model of developing economies suggests that the wealth effect is indeed crucial in understanding the business cycle properties of these economies. We discuss briefly why the adoption of alternative preferences cannot improve the model to explain consumption and labor market dynamics jointly and illustrate how a minimal extension by adding subsistence consumption to the otherwise standard closed economy RBC model better explains the set of empirical stylized facts documented in this paper.

Adoption of alternative preferences. In a class of standard RBC models with KPR preferences (King, Plosser, and Rebelo (1988)), the income effect and the substitution effect of the increase in real wages driven by a positive productivity shock cancel out each other. Since the seminal work by Mendoza (1991), however, the small open economy literature has often adopted GHH preferences by Greenwood, Hercowitz, and Huffman (1988) to generate the countercyclical behavior of the trade balance-to-output and avoid the case where hours fall in response to a rise in trend productivity due to wealth effect. Recently, Jaimovich and Rebelo (2009) develop a utility function (JR preferences) that allows to parameterize the strength of the short-run wealth effect on labor supply, which encompasses both KPR and GHH preferences as polar cases.

Let c_t denote consumption and h_t denote hours worked at period t. The instantaneous utility has the following form:

$$u(c_t, h_t) = \frac{(c_t - \psi h_t^\theta X_t)^{1-\sigma} - 1}{1-\sigma}, \tag{4.1}$$

where $X_t = c_t^\gamma h_t^{1-\gamma}$. It is assumed that $\theta > 1$, $\psi > 0$, and $\sigma > 0$. When $\gamma = 1$, the scaling variable X_t reduces to $X_t = c_t$, and the instantaneous utility function simplifies to

$$u(c_t, h_t) = \frac{(c_t(1 - \psi h_t^\theta X_t))^{1-\sigma} - 1}{1-\sigma}, \tag{4.2}$$

corresponding to KPR preferences. When $\gamma \to 0$ and if the economy does not present exogenous growth, then the scaling variable X_t reduces to a constant $X_t = X > 0$, and the instantaneous utility function simplifies to

$$u(c_t, h_t) = \frac{(c_t - \psi X h_t^{\theta})^{1-\sigma} - 1}{1-\sigma}, \tag{4.3}$$

corresponding to GHH preferences, in which the wealth effect on the labor supply is completely shut off.

In JR preferences, increasing the parameter γ towards one increases short-run wealth effects on the labor supply, thereby dampening the response of hours worked to the technology shock. However, an increase in the parameter γ dampens the response of consumption simultaneously, which is difficult to be reconciled with higher consumption volatility in developing economies. Li (2011) conducts this kind of analysis by varying the parameter γ.[15] As she departs from GHH preferences towards KPR preferences (by increasing γ), the response of consumption to a technology shock in her model decreases and the relative volatility of consumption to output also falls, suggesting that varying the key parameter γ in the JR preferences cannot simultaneously match two salient features about consumption and labor market dynamics (relative variability of consumption and labor to output) in developing economies. Moreovery, varying the parameter γ alone cannot explain the difference in the steady-state behavior of hours worked documented in Bick, Fuchs-Schündeln, and Lagakos (2018).

4.1 Empirical relevance of income-level and subsistence consumption

Then what is a plausible mechanism that explains the set of new empirical stylized facts? To answer this question, we highlight that a poverty line over per-capita income is significantly different across countries. Table 4.1 shows that subsistence consumption-income ratio (poverty line is used as a proxy for subsistence consumption) is not negligible in low- and lower middle-income countries: although subsistence consumption becomes largely irrelevant in advanced economies, it is still an important characteristic of developing economies.

To further highlight its empirical relevance, the left panel in Figure 4.1 plots the correlation between the relative volatility of employment to output (i.e., $\sigma(n)/\sigma(y)$) in 103 countries from

[15] See Table 3 and Figure 7 in Li (2011) for further details.

Table 4.1: Poverty line over per-capita income

Group of countries[a]	GNI per capita[b]	Ratio I[c]	Ratio II[d]
Low-income (31)	1,571	0.44	0.72
Lower middle-income (51)	6,002	0.12	0.19
Upper middle-income (53)	14,225	0.05	0.08
High-income: OECD (32)	43,588	0.02	0.03

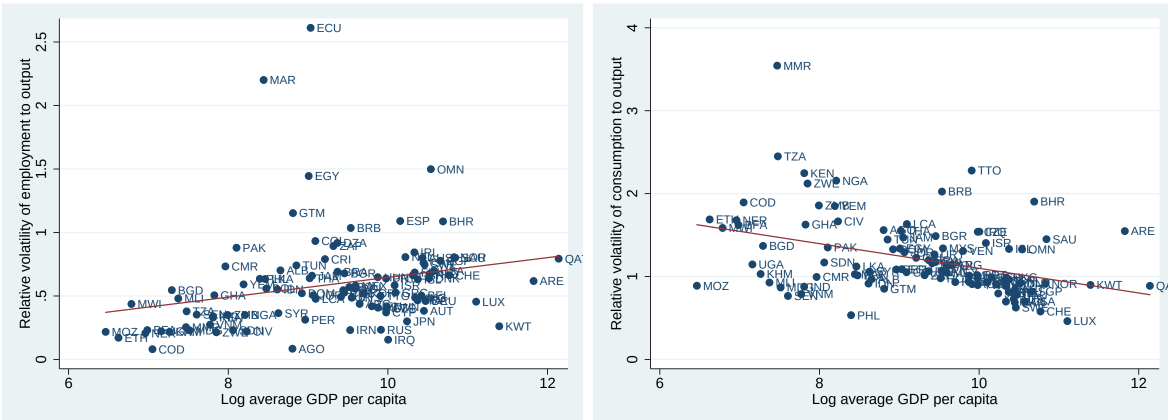
Source: Li, Shim, and Wen (2017).
Note: [a]Country grouping according to the World Bank.
[b]In 2014 dollars.
[c]Ratio between the lower poverty line ($694) and GNI per capita.
[d]Ratio between the upper poverty line ($1,132) and GNI per capita.

1970 to 2014 and the log of the average PPP-adjusted GDP per capita during the same period. By using the PPP-adjusted GDP, we take into account for differences in purchasing power across countries. The correlation is 0.26 and it is statistically significant at 1%.[16] Moreover, the right hand panel in Figure 4.1 shows a strong negative correlation (-0.39 and statistically significant at 1%) between the relative volatility of consumption to output (i.e., $\sigma(c)/\sigma(y)$) and the average PPP-adjusted GDP per capita for the same set of countries, consistent with business cycle properties documented in Table 2.1.

Of course, we do not argue that the income level (or equivalently, subsistence consumption) is the only channel accounting for different dynamics in consumption and labor variables between advance and developing economies. Certainly, other structural factors might also account for the stylized facts documented in Table 2.1. To explore the extent to which subsistence consumption is a relevant factor in explaining the different consumption and labor market dynamics across countries, we test other candidate factors employed in the existing studies to explain distinct business cycle properties of developing economies (Özbilgin (2010); Naoussi and Tripier (2013); Restrepo-Echavarria (2014)). However, previous studies use these structural characteristics to explain volatile business cycles of developing economies with a particular focus on their higher volatility of consumption to output when compared to advanced economies, while remain silent

[16]Although Ecuador and Morocco seem an outlier in terms of the relative volatility of employment to output, they do not drive our findings. Indeed, excluding these two countries from the sample strengthens the role of the income-level even more (the correlation becomes 0.44).

Figure 4.1: GDP per capita and the relative volatility of employment and consumption to output



Note: This figure displays the correlation between the log of average income, measured by PPP-adjusted GDP per capita between 1970 and 2014, and the relative volatility of employment and consumption to output.

about the relative volatility of hours worked or employment to output. We show that other factors known to explain the relative volatility of consumption to output do not perform well in explaining the behavior of labor markets, thereby providing compelling support for the modelling of subsistence consumption.

Based on the existing studies, we choose the following six structural characteristics: (i) trade openness, (ii) private credit provided by the banking sector, (iii) general government final consumption, (iv) the quality of institutions, (v) the degree of labor market regulations, and (vi) the size of the informal economy. These variables have been put forward in the literature as a potential determinant of macroeconomic volatility, thereby serving an alternative explanation for our new empirical findings.

First of all, trade openness is a plausible factor in explaining different consumption and labor market dynamics because it governs the degree of technological spillovers across countries and also the quantitative role of terms of trade shocks (Kose, Prasad, and Terrones (2003)). Second, financial frictions are extensively studied as a source of volatile business cycles of developing economies (Neumeyer and Perri (2005); Uribe and Yue (2006); Garcia-Cicco, Pancrazi, and Uribe (2010); Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramirez, and Uribe (2011); Chang and Fernández (2013); Fernández and Gulan (2015)). Moreover, they are known to contribute to higher volatility of consumption to output of developing economies by preventing efficient consumption smoothing (Özbilgin (2010); Naoussi and Tripier (2013)). Third, the size of governments is also known to be correlated with output volatility (Fatás and Mihov (2001)), which may affect the pattern of consumption and labor market dynamics across countries.

Fourth, we include a measure of institutional quality, which is also one of the most robust factors explaining macroeconomic instability in developing economies (Malik and Temple (2009)). In particular, Aguiar and Gopinath (2007) claim that shocks to trend growth—driven by frequent regime switches resulting in dramatic reversals in fiscal, monetary, and trade policies—are the primary source of fluctuations in developing economies. Fifth, although they are not particularly used to investigate a determinant of macroeconomic volatility, labor market regulations may be an important factor explaining our findings by limiting the response of labor input to the technology shock. Lastly, we consider the size of the informal economy as a potential candidate for explaining our empirical findings: to the extent that the informal economy is poorly measured, its size can affect the relative volatility of consumption to output (Restrepo-Echavarria (2014)).

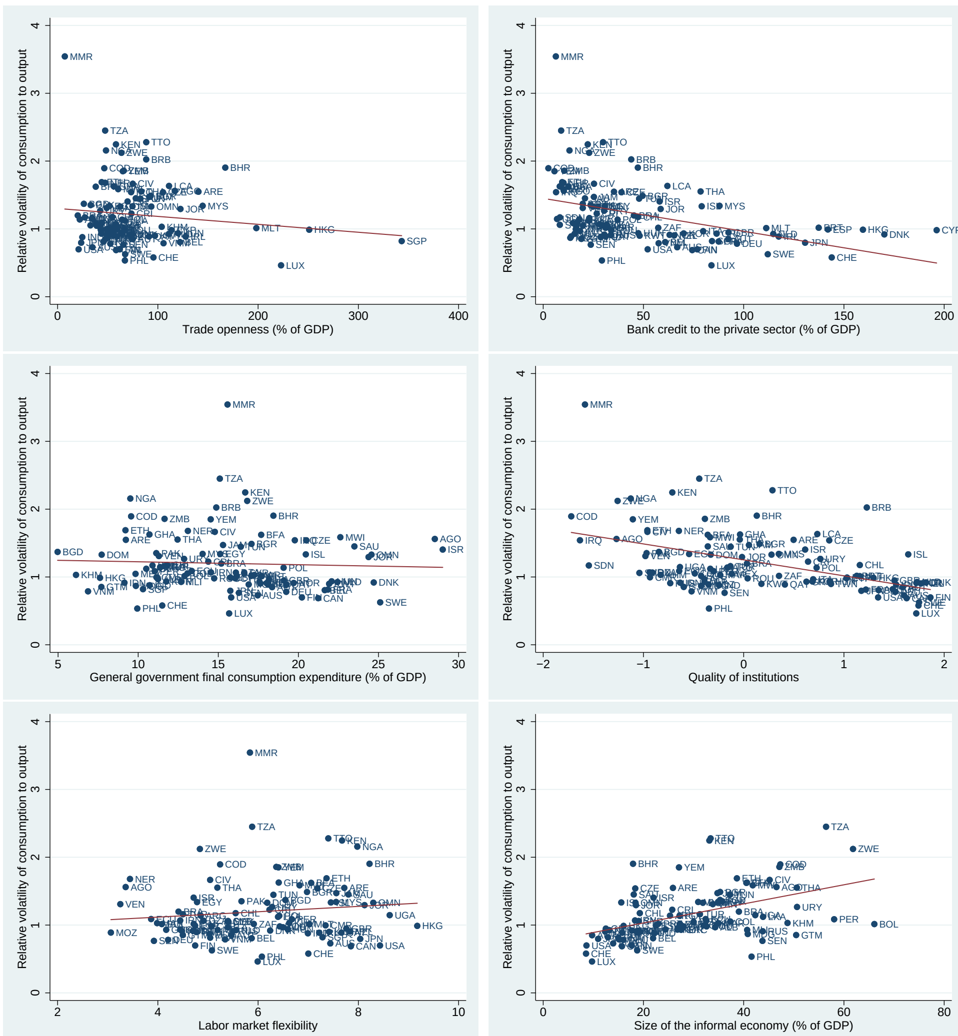
We measure trade openness by the ratio of exports plus imports to GDP as standard in the literature. The degree of financial deepening is measured by the domestic credit provided by banking sector in percentage of GDP, which is also standard in the literature. We use the general government final consumption expenditure in percentage of GDP to measure the size of the government. The three indicators are taken from the World Bank database "World Development Indicators" (WDI).

The quality of institutions is proxied by the "World Governance Indicators (WGI). We use the average value of the six subcategories to measure the comprehensive aspect of the quality of institutions (a higher value indicates a better quality of institutions).[17] To capture institutional differences in labor market regulations across countries, we use the labor market regulation index taken from the Fraser Institutes Economic Freedom of the World (EFW) database, which is computed as the average of six subcategories indicators covering various aspects of labor market regulations, taking a value from 0 (low flexibility) to 10 (high flexibility). Lastly, we use

[17] The six subcategories are (i) control of corruption, (ii) government effectiveness, (iii) political stability and absence of violence/terrorism, (iv) regulatory quality, (v) rule of law, and (vi) voice and accountability.

the widely used index by Schneider, Buehn, and Montenegro (2010) to measure the size of the informal economy. When available, we use the average of each factor over the sample period between 1970 and 2014 in the following exercises.

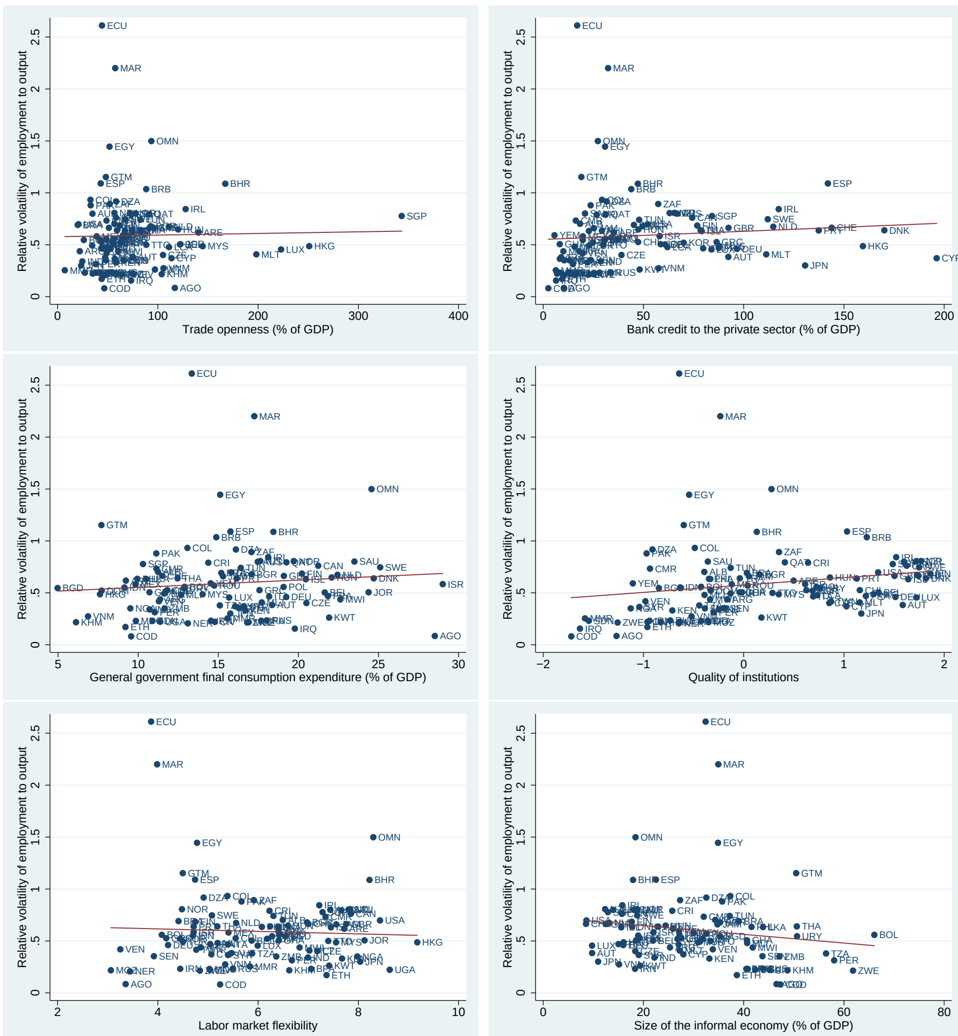
Figure 4.2: The relative volatility of consumption to output and structural characteristics



Note: This figure displays the correlation between the average trade openness from 1970 to 2014 and the relative volatility of employment and consumption to output.

We first plot the correlation between the relative volatility of consumption to output with the six structural characteristics to check whether the previous relationship found in the literature extends to the broader sample of countries used in the paper. Consistent with the literature, Figure 4.2 shows that the degree of financial deepening, institutional quality, and the size of the informal economy is strongly correlated with the relative volatility of consumption to output. The correlations are -0.42, -0.48, and 0.46, respectively and all of them are statistically significant at 1 percent. However, none of the other correlations is statistically significant at 10 percent.

Figure 4.3: The relative volatility of employment to output and structural characteristics



Note: This figure displays the correlation between the average trade openness from 1970 to 2014 and the relative volatility of employment and consumption to output.

Given the lack of systematic attempts to explain the behavior of labor market variables with the same set of structural factors, we contribute to the literature by asking whether these factors jointly explain the relative volatility of employment to output across countries. Interestingly, Figure 4.3 shows that none of these factors successfully accounts for the cross-country heterogeneity in the relative volatility of employment to output. The largest correlation is obtained from the size of the informal economy (-0.14), but its p-value is only 0.16, suggesting that the structural factors known to account for the relative volatility of consumption do not necessarily explain the relative volatility of employment. This finding also narrows down the set of potential modelling approaches to account for our empirical findings.

We formally test the correlation suggested in Figure 4.1-4.3 by estimating the following cross-sectional regression:

$$y_i = \alpha + \beta X_i + \epsilon_i, \tag{4.4}$$

where y_i is the relative volatility of employment (consumption) to output in a country i over 1970-2014 and X_i is a vector of the seven structural factors for a country i. Given the suggestive evidence in Figure 4.1-4.3, we include the average GDP per capita in X_i first, then add each of the rest six structural factors in turn. Finally, we include the seven factors altogether.

Table 4.2: Relative volatility of employment to output and structural factors

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
GDP per capita	0.089***	0.096***	0.099***	0.096***	0.073**	0.086***	0.083***	0.100***
	(0.016)	(0.017)	(0.025)	(0.017)	(0.029)	(0.016)	(0.024)	(0.035)
Trade openness		0.000						-0.001
		0.000						(0.001)
Financial deepening			0.000					-0.001
			(0.001)					(0.001)
Government size				-0.003				-0.003
				(0.006)				(0.006)
Institution quality					0.031			0.022
					(0.040)			(0.054)
Labor regulations						0.000		0.018
						(0.002)		(0.023)
Informal economy							0.015	0.000
							(0.019)	(0.003)
Constant	-0.276*	-0.306**	-0.339*	-0.287*	-0.126	-0.333*	-0.206	-0.366
	(0.149)	(0.148)	(0.195)	(0.151)	(0.254)	(0.191)	(0.268)	(0.419)
Obs	102	101	101	99	102	98	93	92
Adjusted R^2	0.176	0.184	0.183	0.184	0.182	0.192	0.150	0.178

Note: Robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

While we do not claim causality, it is clear from Table 4.2 and 4.3 that the level of average

Table 4.3: Relative volatility of consumption to output and structural factors

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
GDP per capita	-0.150***	-0.153***	-0.083*	-0.182***	-0.038	-0.170***	-0.071*	-0.036
	(0.043)	(0.040)	(0.045)	(0.053)	(0.045)	(0.042)	(0.041)	(0.051)
Trade openness		0.000						0.001
		(0.001)						(0.000)
Financial deepening			-0.003***					0.000
			(0.001)					(0.001)
Government size				0.016*				0.022***
				(0.009)				(0.006)
Institution quality					-0.204***			-0.170**
					(0.057)			(0.065)
Labor regulations						0.011**		0.075***
						(0.004)		(0.025)
Informal economy							0.069*	0.009**
							(0.030)	(0.004)
Constant	2.608***	2.615***	2.151***	2.638***	1.607***	2.356***	1.350***	0.422
	(0.415)	(0.405)	(0.417)	(0.423)	(0.423)	(0.437)	(0.511)	(0.551)
Obs	102	101	101	99	102	98	93	92
Adjusted R^2	0.158	0.156	0.215	0.200	0.247	0.212	0.235	0.439

Note: Robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

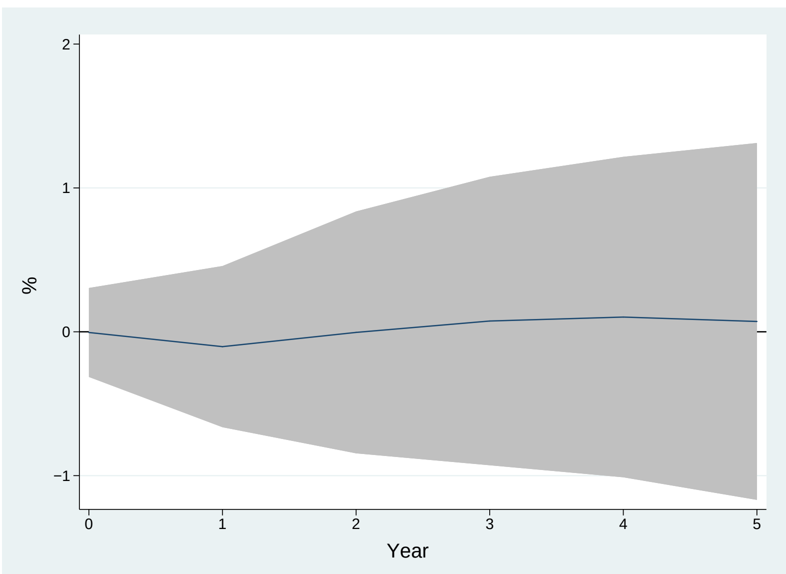
PPP-adjusted income per capita, or equivalently, the level of subsistence consumption is the most robust factor in explaining jointly the cross-country differences in the relative volatility of employment and consumption to output.

Empirical relevance of subsistence consumption over time. As already illustrated, the size of the response of hours worked to a technology shock depends on the relative size between the substitution and income effect. As Bick, Fuchs-Schündeln, and Lagakos (2018) point out, the role of subsistence consumption in determining the size of the income effect becomes smaller as actual consumption level rises. In other words, the income effect becomes smaller in high-income economies as subsistence consumption becomes less binding, which implies that subsistence consumption can be a plausible candidate to explain our empirical findings. Moreover, Ohanian, Raffo, and Rogerson (2008) find that the standard growth model appended to include taxes and a modest subsistence consumption effect performs better in capturing the large differences in trend changes in hours worked across countries, both in terms of the overall change in hours and the timing of the changes. Their findings also suggest the important role played by subsistence consumption in explaining the behavior of hours worked.

One might argue that the subsistence consumption channel is irrelevant for middle-income countries anymore and these countries are the one often studied in the emerging market business cycle literature. However, most studies on emerging market economies focus the period since 1990 due to the limited data availability, mainly on interest rates.[18] Given that many of middle-income emerging market economies were still quite poor until the 1980s, our choice of the sample period from 1970 largely mitigates this concern.

To further highlight the role of subsistence consumption in explaining labor market dynamics, we present the structural VAR results using the earlier data on a group of advanced economies from 1950 to 1970. As shown in Figure 4.4, the response of hours worked to the world permanent technology shock is muted even in advanced economies during the period in which subsistence consumption is likely to matter.

Figure 4.4: IRF of hours worked to the world permanent technology shock: 1950-1970



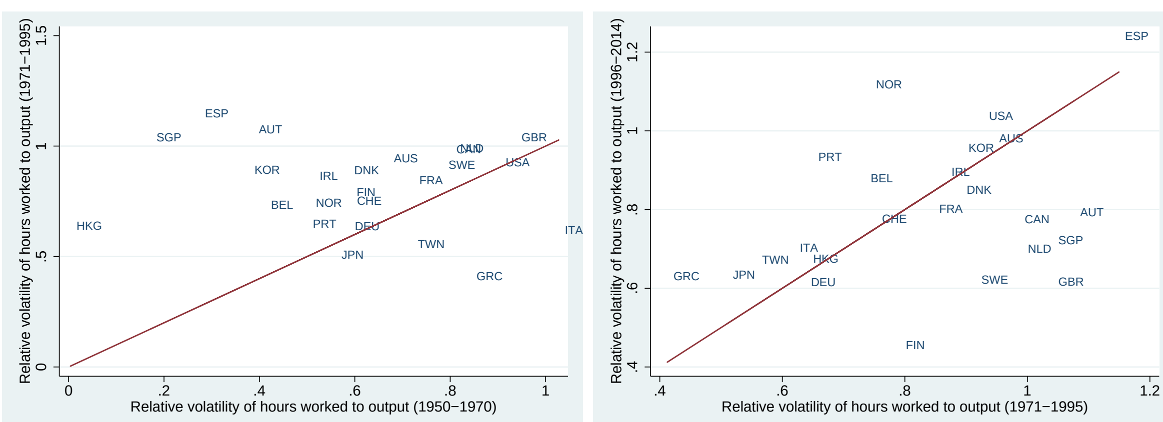
Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{World,h}, \Delta h_t^{Advanced}$) and its 90% confidence interval from 500 bootstraps.

Lastly, we show that the relative volatility of hours worked to output—one of the key business

[18]Notable exceptions are Garcia-Cicco, Pancrazi, and Uribe (2010) and Miyamoto and Nguyen (2017).

cycle properties distinguishing high-income countries from low-income countries—also increases over time in advanced economies.[19] The left panel in Figure 4.5 compares the relative volatility of hours worked to output during the period 1950-1970 when subsistence consumption was likely relevant even for advanced economies with that during 1971-1995. A country above the 45 degree line indicates that the relative volatility of hours worked to output increases over time. Despite much heterogeneity in their institutional characteristics and labor market regulations, advanced economies share an interesting pattern. As subsistence consumption loses its relevance for this group of countries, the relative volatility of hours worked to output increases with only few exceptions. However, the right panel in Figure 4.5 shows that once subsistence consumption becomes largely irrelevant for advanced economies after 1970s, additional economic growth is not associated with an increase in the relative volatility of hours worked to output.[20] Such an interesting pattern found in time-series data supports the claim that subsistence consumption is key to understanding the distinct business cycle properties of developing economies.

Figure 4.5: Relative volatility of hours worked to output over time



Note: This figure displays the correlation between the relative volatility of hours worked to output during 1950-1970 and the relative volatility of hours worked to output during 1971-1995 (left) and the correlation between the relative volatility of hours worked to output during 1971-1995 and the relative volatility of hours worked to output during 1996-2014 (right).

[19]While most of the data on developing economies are available from 1970, they are often available from 1950 for advanced economies. In this exercise, we use 24 advanced economies where hours worked data are available since 1950.

[20]The cross-country average of the relative volatility of hours worked to output in each period (1950-1970, 1971-1995, 1996-2014) is 0.59, 0.82, and 0.80, respectively.

In the following section, we check whether our simple extension of the RBC model by embedding subsistence consumption can explain the set of empirical regularities we documented. We first lay out a simple static model to grasp an economic intuition and then discuss the implication of a subsistence consumption-augmented dynamic RBC model.

4.2 Intuition from a static model

In this section, we present a static model to help understand the key mechanism of our model. Consider the following household utility maximization problem:

$$\max_{c,h} \frac{(c-\bar{c})^{1-\sigma}-1}{1-\sigma} - h \tag{4.5}$$

subject to a resource constraint $c = Zh$ where $\bar{c} \geq 0$ is the level of subsistence consumption and $Z > 0$ denotes the level of productivity. We assume that $\sigma < 1$ for this analysis, which is relaxed later.

Solution to the above model is given by

$$h^* = Z^{1/\sigma - 1} + \frac{\bar{c}}{Z} \tag{4.6}$$

and $c^* = Zh^*$.

As we are interested in the response of hours worked to a technology shock, we differentiate the equation (4.6) with respect to Z:

$$\frac{dh^*}{dZ} = \frac{1-\sigma}{\sigma} Z^{1/\sigma - 2} - \frac{\bar{c}}{Z^2} \tag{4.7}$$

Suppose that $\bar{c} = 0$ as in the standard RBC model. Under the assumption that $\sigma < 1$, hours worked increases unambiguously as productivity increases, which is the main prediction of the standard RBC model. However, as the subsistence level of consumption $\bar{c}$ increases, the response of hours worked to the technology shock becomes smaller. Given that subsistence consumption is more important in less-developed economies (Table 4.1), this equilibrium property implies that there is a potential for the subsistence consumption-augmented model to explain our main empirical finding.

Then what is the underlying mechanism of the smaller response of hours worked to the technology shock? The important channel, which we call a 'subsistence consumption' channel, is captured by the equation (4.6). h^* increases with $\bar{c}$, which is a natural consequence of introducing subsistence consumption. Workers should work more to keep up their consumption level above the subsistence level. Thus, disutility from working is higher in the economy with higher subsistence consumption. Suppose that there is a positive technology shock. As a worker supplies a lot of labor already, she cannot further increase her supply of labor as much as she wants when productivity is higher. On the contrary, although a negative technology shock makes leisure becomes more attractive, she cannot reduce her labor supply because she should maintain consumption above the subsistence level.

4.3 Main Model

This section introduces a dynamic subsistence consumption-augmented RBC model. We consider the following social planner's problem:

$$\max_{c_t,k_{t+1},h_t} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\ln\left(c_t - \bar{c}\right) - \psi \frac{h_t^{1+\phi}}{1+\phi} \right], \tag{4.8}$$

subject to

$$c_t + k_{t+1} = Z_t k_t^{1-\alpha} h_t^{\alpha} + (1-\delta) k_t \tag{4.9}$$

where $\beta \in (0,1)$ is the discount factor, c_t is period t consumption, $\bar{c} \geq 0$ denotes the subsistence level of consumption, and h_t represents hours worked at period t. In addition, $\phi > 0$ is the inverse of Frisch labor elasticity, $\psi > 0$ is the preference parameter, $\delta \in (0,1)$ is the rate of depreciation, $\alpha \in (0,1)$ is the labor share, k_t denotes period t capital stock, and Z_t denotes a technology shock, which follows an AR (1) process:

$$\ln Z_t = \rho \ln Z_{t-1} + \varepsilon_t, \tag{4.10}$$

where $\rho \in (0,1)$ and $\varepsilon_t \sim N(0, \sigma_z^2)$.

Subsistence consumption is incorporated in the utility function as a Stone-Geary form; log utility is considered to guarantee the balanced growth path of our model (King, Plosser, and Rebelo (2002)). However, as shown by Li, Shim, and Wen (2017), using CRRA type utility function for consumption does not alter the equilibrium property of the model. When solving the model with the perturbation method (Schmitt-Grohé and Uribe (2004)), we define $\tilde{c}_t \equiv c_t - \bar{c}$ and use it in the following analysis.[21]

Calibrated parameter values are reported in Table 4.4. We note that our results do not depend much on the parameter values. In addition, we set ψ to ensure steady-state hours worked, h, is $1/3$ when $\bar{c} = 0$.

Table 4.4: Calibrated parameters

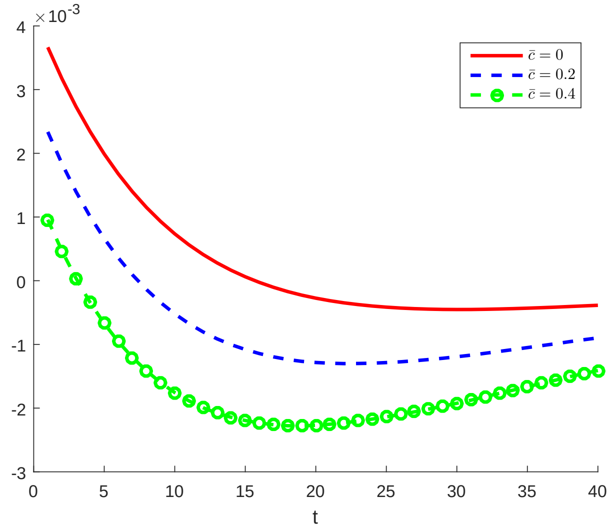
Parameter	Value	Description
β	0.955	Discount factor
ϕ	1	Inverse Frisch elasticity
α	0.67	Labor income share
δ	0.02	Rate of capital depreciation
ρ	0.95	AR (1) coefficient
σ	0.01	std of TFP shock

Predictions of the model. We first test if the behavior of our model is consistent with the stylized facts observed in developing economies. Figure 4.6 plots impulse response functions of hours worked to one-time-one-unit shock to technology. If subsistence consumption is zero, the model economy collapses to a standard RBC economy. Therefore, it is natural to observe a positive response of hours worked to the technology shock (solid red line). However, as we increase the subsistence level of consumption, the response of hours worked to the technology shock becomes smaller at any point, which implies that workers in the economy with high subsistence consumption respond less to the positive productivity shock. Thus, the RBC model with subsistence consumption can reproduce our novel empirical finding. It is also consistent

[21] Note that $c_t = \tilde{c}_t + \bar{c}$ implies $\sigma(c_t) = \sigma(\tilde{c}_t)$ as $\bar{c}$ is constant.

with Bick, Fuchs-Schündeln, and Lagakos (2018) who find a positive relationship between the income-level and hours-wage elasticity.[22]

Figure 4.6: Response of hours worked to a technology shock: Model prediction



A next question is whether our model behaves well in other dimensions. In particular, we check if our model can match the well-known facts about developing economy business cycles. As our model is the minimal extension of a standard closed-economy RBC model, we do not discuss other characteristics, such countercyclical net exports and interest rates. Again, compared to advanced economies, developing economies share the following business cycle properties:

1. Hours worked is higher (Bick, Fuchs-Schündeln, and Lagakos (2018))
2. $\sigma(c)/\sigma(y)$ is higher (Aguiar and Gopinath (2007))
3. $\sigma(w)/\sigma(y)$ is higher (Boz, Durdu, and Li (2015))
4. $\sigma(h)/\sigma(y)$ is lower (Boz, Durdu, and Li (2015))

[22]Following Costa (2000), Bick, Fuchs-Schündeln, and Lagakos (2018) regress the log of individual hours worked on the log wage within each country and compare this country-specific hours-wage elasticity with the country's income level. They find a negative (positive) elasticity for low-income (high-income) countries.

Figure 4.7 plots the relationship between variables of interest and the subsistence consumption to income ratio by varying $\bar{c}/y$ from zero (corresponding to a high-income country) to 0.5 (corresponding to a low-income country). The solid red line in Figure 4.7a shows that steady-state hours worked is increasing in subsistence consumption. The intuition is already discussed in the previous section. The green dotted line and the blue dotted line describe how the relative volatility of hours worked to output and the relative volatility of real wage to output vary with $\bar{c}/y$, respectively. They replicate the empirical regularity found in Figure 4.1 and 4.2 successfully and also corroborate the findings of Boz, Durdu, and Li (2015).

Figure 4.7: Dynamics of the model economy

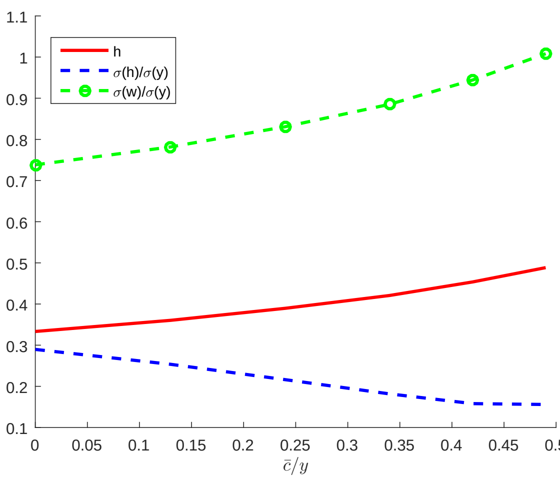


Figure 4.7a: Labor market behaviors

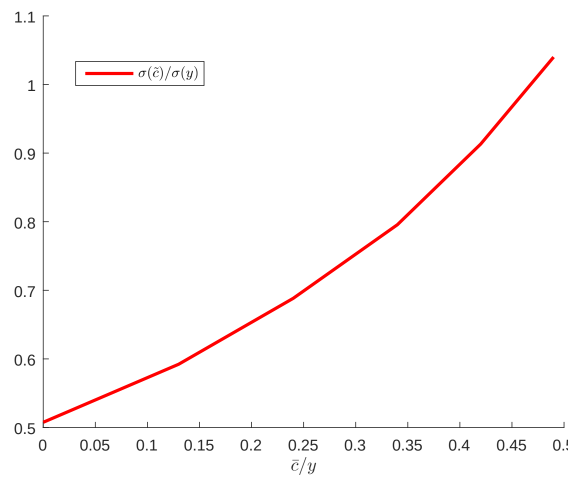
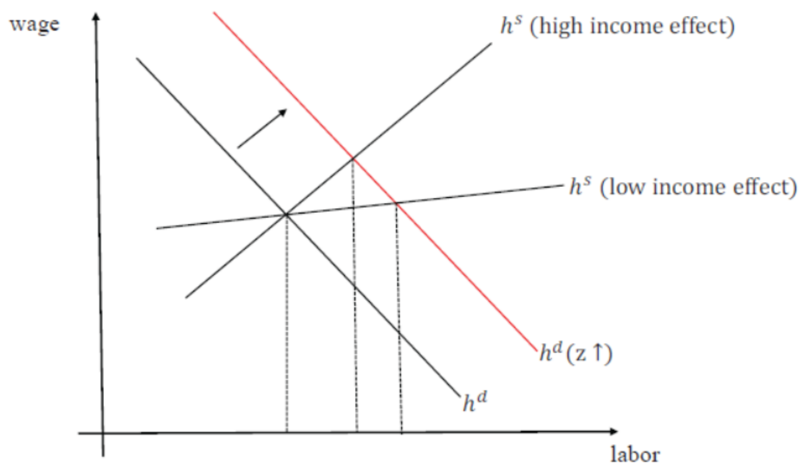


Figure 4.7b: Relative volatility of consumption

As Bick, Fuchs-Schündeln, and Lagakos (2018) point out, the introduction of subsistence consumption increases the income effect. Conceptually, this implies that slope of labor supply curve becomes steeper (hours worked responds less to a given change in real wage; see Figure 4.8). With a steeper labor supply curve, (i) hours volatility declines but (ii) wage volatility increases as the subsistence consumption level rises. The response in the green dotted line can also be understood by the similar logic. Lastly, a positive relationship between consumption volatility and subsistence consumption is straightforward. Given large changes in wage and small changes in hours worked, the labor supply equation that equates real wage and marginal rate of substitution between consumption and leisure implies that consumption should increase further to match the greater wage response in the economy with higher subsistence consumption.

Figure 4.8: Description of the labor market



5 Conclusion

Applying a structural VAR model with long-run restrictions to the long time-series data of both advanced and developing economies, we document a novel empirical finding that the response of hours worked (and employment) to a permanent technology shock is smaller in developing economies than advanced economies. Together with the other business cycle properties of developing economies that the relative variability of hours worked (real wage) to output is smaller (greater) than that of advanced economies, our finding challenges the ability of the existing models to explain distinct labor market dynamics. In particular, introducing GHH preferences—a common practice in the emerging market business cycle literature since Mendoza (1991)—to match the relative volatility of consumption to output by shutting down the income effect is in sharp contrast to our finding about the labor market response to the technology shock.

To resolve this problem, we claim that 'subsistence consumption, whose importance is greater in less-developed economies, is the key to understanding our findings. While our simple model abstracts from other interesting properties of developing economy business cycles, such as countercyclical interest rates and net exports, it is the first attempt to evaluate the role of subsistence consumption in explaining labor market dynamics in developing economies. Further research is needed to incorporate other important features of these economies, such as financial frictions, to our model in order to reproduce a wider set of business cycle properties.

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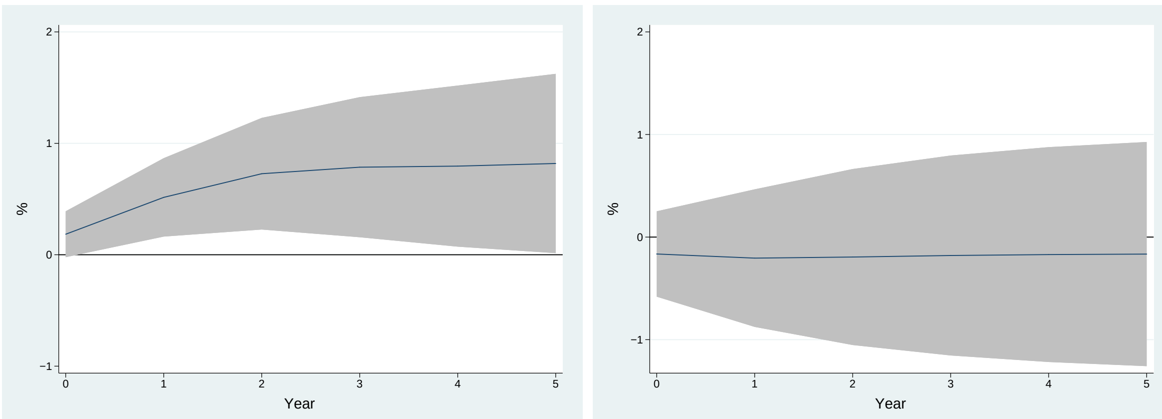
Appendix

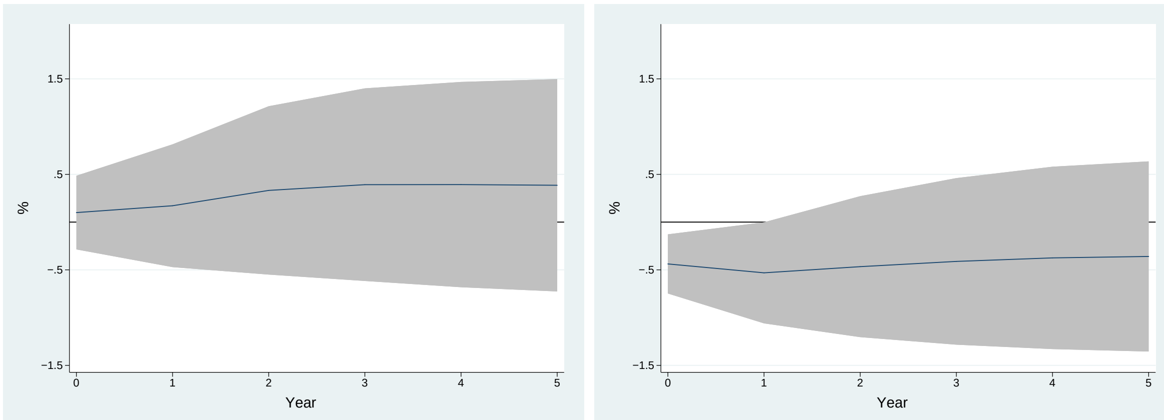
A Additional figures and tables

Figure A.1: IRF of total employment to the group-specific permanent technology shock



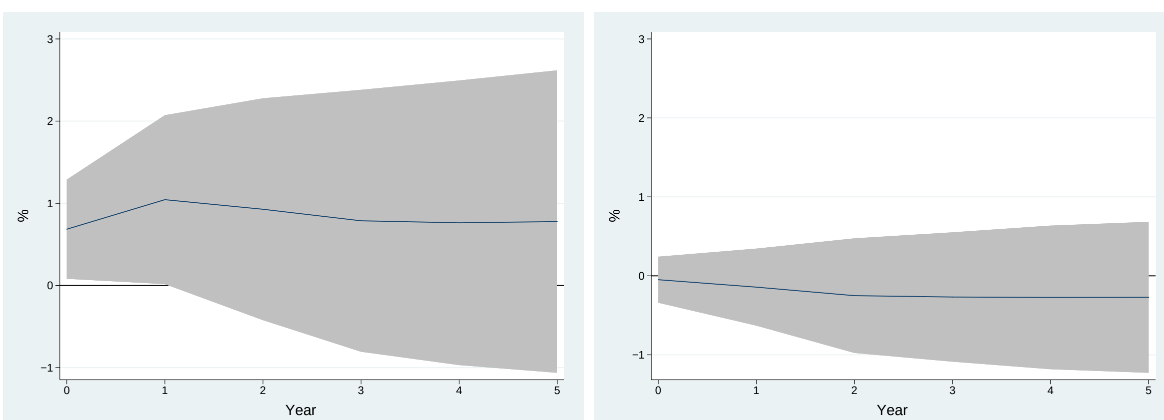
Note: This figure displays the impulse response function of total employment to the permanent group-specific technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{Advanced,n}, \Delta n_t^{Advanced}$) in the left panel and developing economies ($\Delta z_t^{Developing,n}, \Delta n_t^{Developing}$) in the right panel and its 90% confidence interval from 500 bootstraps.

Figure A.2: IRF of hours worked to the permanent technology shock in developing economies: without LICs (left) and using advanced economy technology shock instead (right)



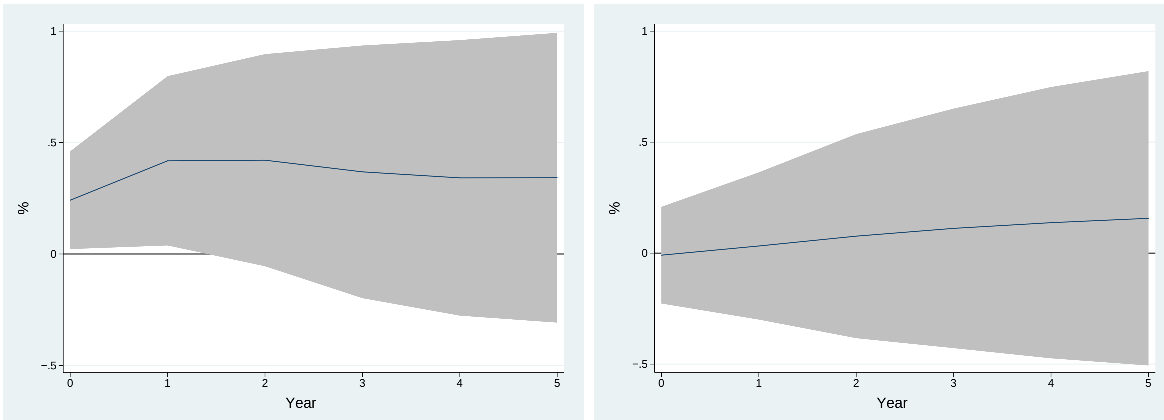
Note: This figure displays the impulse response function of hours worked to a permanent world technology shock in a bivariate VAR model of emerging economies without low-income countries ($\Delta z_t^{World,h}, \Delta h_t^{Emerging}$) in the left panel and the impulse response function of hours worked to a permanent advanced economy technology shock in a bivariate VAR model of developing economies ($\Delta z_t^{Advanced,h}, \Delta h_t^{Developing}$) in the right panel and its 90% confidence interval from 500 bootstraps.

Figure A.3: IRF of hours worked to the world permanent technology shock since 1985



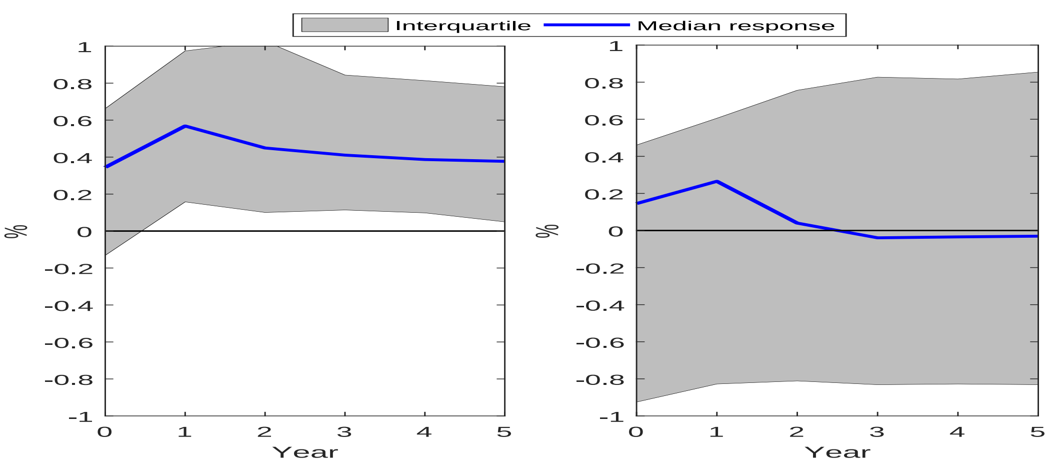
Note: This figure displays the impulse response function of hours worked to a permanent world technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{World,h}, \Delta h_t^{Advanced}$) in the left panel and developing economies ($\Delta z_t^{World,h}, \Delta h_t^{Developing}$) in the right panel from the sample period since 1985 and its 90% confidence interval from 500 bootstraps.

Figure A.4: IRF of total employment to the world permanent technology shock using the full sample



Note: This figure displays the impulse response function of total employment to a permanent world technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{World,n}, \Delta n_t^{Advanced}$) in the left panel and developing economies ($\Delta n_t^{World,n}, \Delta n_t^{Developing}$) in the right panel using the full sample of 103 countries (31 advanced vs. 72 developing economies) and its 90% confidence interval from 500 bootstraps.

Figure A.5: Country-by-country IRF of hours worked to the world permanent technology shock: adding productivity differentials



Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a trivariate VAR model ($\Delta z_t^{World,h}, \Delta h_{i,t}, \Delta z_{i,t}^h - \Delta z_t^{World,h}$,). The left panel shows the interquartile distribution of advanced economies and the right panel shows the interquartile distribution of developing economies.

Table A.1: The list of countries in the baseline analysis

Advanced economies	Developing economies	
Australia	Albania	Malaysia
Austria	Algeria	Mali*
Belgium	Angola	Mexico
Canada	Argentina	Morocco
Cyprus	Bahrain	Mozambique*
Czech Republic	Bangladesh*	Myanmar*
Denmark	Barbados	Niger*
Finland	Bolivia*	Nigeria*
France	Brazil	Oman
Germany	Bulgaria	Pakistan
Greece	Burkina Faso*	Peru
Hong Kong	Cambodia*	Philippines
Iceland	Cameroon*	Poland
Ireland	Chile	Qatar
Israel	China	Romania
Italy	Colombia	Russian Federation
Japan	Costa Rica	Saudi Arabia
Luxembourg	Cte d'Ivoire*	Senegal*
Malta	Dominican Republic	South Africa
Netherlands	DR Congo*	Sri Lanka
New Zealand	Ecuador	St. Lucia
Norway	Egypt	Sudan*
Portugal	Ethiopia*	Syria
Singapore	Ghana*	Tanzania*
South Korea	Guatemala	Thailand
Spain	Hungary	Trinidad and Tobago
Sweden	India	Tunisia
Switzerland	Indonesia	Turkey
Taiwan	Iran	Uganda*
United Kingdom	Iraq	United Arab Emirates
United States	Jamaica	Uruguay
	Jordan	Venezuela
	Kenya*	Vietnam*
	Kuwait	Yemen*
	Madagascar*	Zambia*
	Malawi*	Zimbabwe*

Note: * denotes a country belonging to the low-income category.

B Alternative modelling approach

In the main body of the paper, we have shown that a minimal departure from a standard RBC model—by augmenting subsistence consumption—can explain the salient features of consumption and labor market dynamics in developing economies. However, since this approach is not necessarily the only way to explain the salient features of the data, we review alternative models briefly and test whether they can explain the set of empirical stylized facts. We do not necessarily discuss every element of each model for the brevity of the paper.

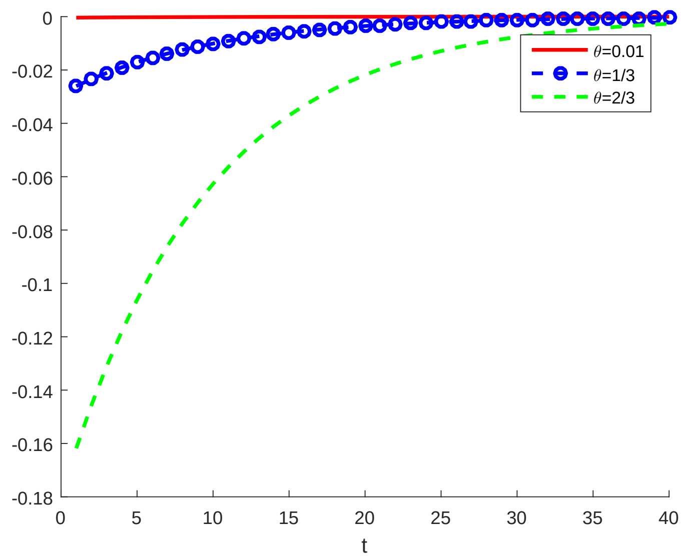
B.1 New Keynesian model with nominal price rigidities

The first natural candidate to explain our empirical findings is the degree of price rigidities. Given that the negative response of hours worked to the permanent technology shock in Galí (1999) advocates the explanation based on a class of new Keynesian models with nominal price rigidities, one might argue that price rigidities in developing economies are responsible for the smaller response of hours worked to the permanent technology shock found in this paper.

To test this hypothesis, we consider a canonical three-equation New Keynesian model as in Galí (2008), which consists of a dynamic IS equation, a New Keynesian Phillips curve, and a Taylor rule governing monetary policy. Details of the model are referred to Galí (2008). To see the implication of price rigidities, we vary the Calvo parameter, denoted as θ. Lower θ implies that prices become more flexible (fraction of firms that can adjust price is denoted by $1 - \theta$). Figure B.1 plots the IRFs of hours worked to a positive technology shock. The response of hours worked becomes smaller as prices become more sticky, suggesting that price rigidities might explain our findings.

However, there are two problems in this explanation. First, we cannot find reliable empirical evidence that firms in developing economies are more constrained in changing their prices. Even if it is the case, this model cannot match the new stylized fact that the level of hours worked is higher in these economies. This is because steady-state hours worked is independently determined from the choice of θ, the Calvo parameter. The real marginal cost is not a function of the Calvo

Figure B.1: Response of hours worked to a technology shock: New Keynesian model with varying nominal price rigidities



parameter, but a function of a markup at the steady-state instead.[23]

B.2 Model with trend growth shocks

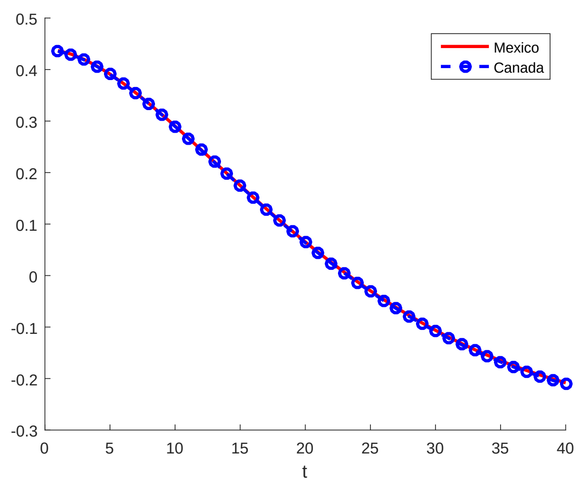
Another strand of the literature on emerging market business cycles has introduced an alternative shocks, such as a shock to trend growth (Aguiar and Gopinath (2007) among others) to explain their distinct business cycle properties. In this section, we discuss whether these models can explain our new empirical finding. We first test whether the model by Aguiar and Gopinath (2007) can generate a set of the stylized facts regarding labor market dynamics documented in the previous section. Instead of summarizing their model in details, we simply show that the response of hours worked to a technology shock implied by the model is the same between advanced and developing economies. Note that their model is a standard single-good and single-asset small open economy model, but augmented to include both transitory and trend shocks to productivity. The inclusion of a trend productivity shock is motivated by the frequent policy

[23] In particular, one can show that $n = \frac{\phi+1-(1-\alpha)(\sigma-1)}{\log(1-\alpha)-\mu}$ in the model introduced in Section 3 of Galí (2008). We also use a medium-scale New Keynesian model and find that the steady-state hours worked does not depend on the Calvo parameter. The results are available upon request.

regime switches observed in emerging market economies. We consider a transitory productivity shock in the exercise so that the results are comparable with other exercises in the paper.[24]

In their paper, two particular countries representing each group of countries are compared; Canada and Mexico. We use their model to obtain the IRFs of hours worked to the technology shock for each country and report them in Figure B.2.[25] It is clear that the model with a trend shock cannot reproduce different labor market dynamics in Mexico (representing a typical small open developing economy) from Canada (representing a typical small-open advanced economy. This is because of the success of their model is driven by the introduction of additional shocks to reproduce the observed second moments (and (auto-) correlations) and the labor market structure is (i) exactly equivalent to the standard RBC model and (ii) identical between the two economies (Mexico and Canada) so that the response of hours worked to the technology shock is also identical.

Figure B.2: Response of hours worked to a technology shock: Aguiar and Gopinath (2007) model



[24]We also interpret a trend shock as a permanent technology shock in the structural VAR analysis in the previous section and analyze the response of hours worked to the trend shock. The results are still identical to those obtained here.

[25]For this exercise, we extend the Dynare code kindly shared by Johannes Pfeifer and confirm that the model economy simulated from the code successfully replicates the key figures and tables in Aguiar and Gopinath (2007).

B.3 Model with financial frictions

Another possibility is that developing economies are subject to tighter financial constraints than advanced economies, which limit the labor choice of households in developing economies. Indeed, a large body of the literature has emphasized the role of financial frictions in these economies to explain their distinct business cycle properties (Neumeyer and Perri (2005); Garcia-Cicco, Pancrazi, and Uribe (2010); Chang and Fernández (2013); Fernández and Gulan (2015)). To check this possibility, we consider a version of Iacoviello (2015) model.[26]

Again, we are abstract from the description of the full model. Instead, we discuss briefly how financial frictions are introduced into the model. First, impatient households face a borrowing constraint when buying houses. Second, entrepreneurs face similar a borrowing constraint. Let us consider the following simplified borrowing constraints for the entrepreneur (producer of this economy) to get an intuition:

$$l_t^e \leq \gamma^H \mathbb{E}_t \frac{P_{t+1}^e H_t}{r_{t+1}} + \gamma^K K_t - \gamma^N (w_t^s N_t^s + w_t^b N_t^b), \tag{B.1}$$

where l_t^e denotes loan made by the entrepreneur, γ^H, $\gamma^K \in (0,1)$ are collateral constraint on housing (H_t) and physical capital (K_t) that the entrepreneur owns. $\gamma^N(w_t^s N_t^s + w_t^b N_t^b)$ means that a fraction (γ^N) of labor income must be paid in advance.

We vary γ^K to capture the degree of financial constraints.[27] Now entrepreneurs can borrow less as γ^K decreases (less physical capital can be pledged), which implies tighter financial constraints. The response of hours worked to a positive technology shock that we are interested in is presented in Figure B.3.

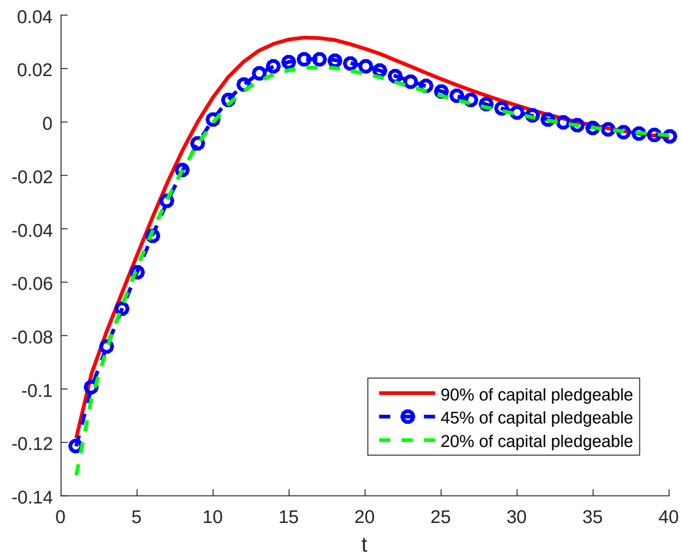
Note that hours worked responds negatively in this model because we use the New Keynesian version of the model by Iacoviello (2015). While the response of hours worked is smaller with a lower value of γ^K (describing developing economies), the difference across the economies does not seem critical even when we impose unrealistically tight borrowing constraints.[28] The intuition

[26] In particular, we use the model extended by Mok and Shim (2017) that extends the original model of Iacoviello (2015) by embedding nominal price rigidities.

[27] The results are qualitatively similar when varying γ^H that captures the degree of financial frictions.

[28] In a related study by Miyamoto and Nguyen (2017) using long time-series data spanning over 100 years from

Figure B.3: Response of hours worked to the technology shock: Iacoviello (2015) model



is as follows. Suppose that financial frictions are very severe so that workers (or firms) cannot access financial markets at all. Then labor income becomes more important for these workers so that higher wage driven by a positive productivity shock cannot induce a large enough income effect, which is necessary to dampen the response of hours worked to the technology shock.

a group of both developed and developing economies, the degree of financial frictions implied by the Bayesian model estimation is not substantially different between the two groups.