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

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Abstract

Motivated by recent empirical evidence on a strong negative relationship between the income-level and hours worked across and within 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 associated with labor market properties 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, which have been largely overlooked.

JEL classification: E21; E32; F44; J20

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

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1 Introduction

Business cycles in developing economies are often characterized by higher variability of consumption and real wages 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 higher relative variability of consumption and real wages in the former group. Moreover, in the independent stream of research, Bick, Fuchs-Schündeln, and Lagakos (2018) document that average hours worked per adult are substantially higher in low-income countries than in high-income countries, suggesting that not only business cycle properties, but are the steady-state characteristics of labor markets in developing economies distinct from developed economies.

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 (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 fall in response to a rise in trend productivity due to wealth effect. However, the marginal rate of substitution between consumption and

[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.

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. Because labor 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.

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 despite the extensive literature on developing economy business cycles listed above. 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 and the business cycle properties regarding consumption and labor. Interestingly, other potential candidates, such as openness or labor market regulations, fail to explain 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 can explain better 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 is an important candidate to explain the difference between the two groups. To the best of our knowledge, however, subsistence consumption has not been used to explain a distinct feature of developing economy business cycles.[2]

We find that the equilibrium properties of our model are consistent with 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 technology shocks becomes smaller, which is consistent with our finding. We further show that the model-implied business cycle properties, including greater wage (and consumption) volatility relative to output and smaller hours worked volatility relative to output, are also consistent with the data. Moreover, the recent observation that workers work more in lower-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 in such economies, the effective slope of the labor supply curve becomes steeper. As a result, with the technology shock of the same magnitude shifting the labor demand curve out, hours worked respond less in the economy with a high level of subsistence consumption. Moreover, workers supply a high level of labor at the steady state to maintain their consumption above the subsistence level. 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 lower labor supply in response to a negative technology shock because of the binding subsistence level. 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.

We also check whether an alternative class of models can explain our findings. First, we test whether a standard new Keynesian model with nominal price rigidities can explain our finding. Galí (1999) shows that introducing price rigidities to a standard dynamic model helps explain a negative response of hours worked to technology shocks. While the variation in the degree of price rigidities—captured by the Calvo type pricing behavior—can match our findings qualitatively, there are two problems associated with this approach. First, there is no empirical evidence that nominal prices are more rigid in developing economies. Second, this model cannot explain the new stylized fact from Bick, Fuchs-Schündeln, and

[2] See Ravn, Schmitt-Grohe, and Uribe (2008) for their use of subsistence consumption to explain countercyclical mark-ups.

Lagakos (2018) that workers work more in lower-income countries.

Second, we show a model with trend productivity shocks such as Aguiar and Gopinath (2007) cannot reproduce our finding about labor market dynamics. We find that the response of hours worked to the technology shock implied by the model remains essentially the same when the underlying parameters are calibrated to match the business cycle moments of developing economies.

Third, we show that a simple New Keynesian model with financial frictions such as Iacoviello (2015) cannot reproduce our empirical findings. Despite the fact that developing economies are often characterized by more frictions regarding the access to the financial markets, introducing more financial frictions to the model fails to match the properties of consumption and labor simultaneously.[3]

Lastly, we discuss the implication of introducing the preferences developed by Jaimovich and Rebelo (2009), which nest both KPR (King, Plosser, and Rebelo (1988)) and GHH preferences (Greenwood, Hercowitz, and Huffman (1988)). While deviating from GHH preferences towards the KPR preferences can dampen the response of hours worked to the technology shock, it also dampens the response of consumption, thereby contradicting the most salient feature of developing economy business cycles. Thus we conclude that a wide class of DSGE models is lack of an important mechanism to explain labor market dynamics in developing economies.

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 in Section 3. Section 4 introduces our RBC model with subsistence consumption and demonstrates its empirical relevance. In Section 5, we further discuss if existing theories can explain our findings. Section 6 concludes.

2 Data

We use 45 years of annual data on labor productivity, total hours worked, and employment for the sample period 1970-2014 in our baseline empirical analysis. While using higher frequency data is ideal, it reduces both the cross-sectional and time-series coverage of the data substantially, especially for developing economies. Still the 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

[3] Moreover, in a related study by Miyamoto and Nguyen (2017) using long time-series data spanning over 100 years from 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.

50 years, but only for 14 OECD countries.[4]

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, paid vacation and sick days, and days lost due to strikes, and are consistent with NIPA measures of output.[5]

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.[6] Table A.1 in the appendix presents the full list of countries used in the robustness check using employment data.[7] Compared to advanced economies, developing economies are characterized by smaller relative variability of both

[4] In the previous draft 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. Nevertheless, we choose annual hours worked data over quarterly employment data in the baseline analysis to capture the both intensive and extensive margins of labor and be consistent with earlier structural VAR analysis on advanced economies, such as Christiano, Eichenbaum, and Vigfusson (2004), Galí (2004), and Basu, Fernald, and Kimball (2006).

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

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

[7] 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.

hours worked and employment to output, which corroborates the empirical stylized fact in Neumeyer and Perri (2005) and Boz, Durdu, and Li (2015), but using a substantially larger sample.[8]

3 Empirical Analysis

The new stylized facts regarding the business cycle properties of developing economies suggest that some frictions in their labor markets prevent adjusting labor input to exogenous shocks. Among a group of exogenous shocks hitting the economy, we take a simplest approach and analyze the behaviors 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. 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 of 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 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, Bordo and Helbling (2003), Kose, Prasad, and Terrones (2003), Kose, Otrok, and Whiteman (2003), and Stock and Watson (2005) find the large contribution of world common shocks to macroeconomic variables in individual countries by estimating a factor model.[9] 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 interestingly, common shocks are of similar importance for both groups of countries, suggesting that the importance of world common shocks is not restricted to developed economies.

[8] 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.

[9] 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.

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

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.[10] The aggregation across countries offsets the country-level stationary shocks which contaminate country-level data, thereby mitigates identification problems.

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 major seven countries from 1978 to 2003. When estimated with country-level quarterly data on the growth rates 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, where 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.

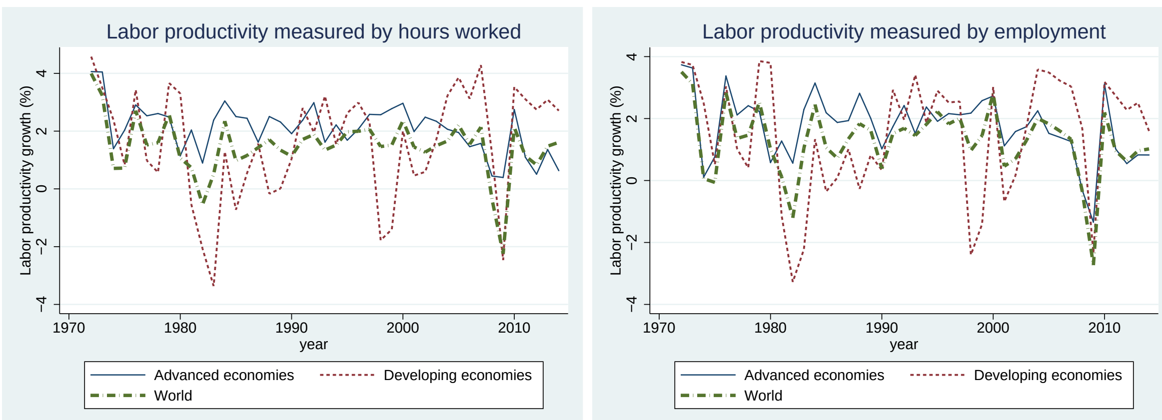
Based on the estimation of the data generated by a structural model, Dupaigne and Fève (2009) argue that a measure of labor productivity aggregated across countries improves the identification of the response of the labor input to a technology shock in the international context. Moreover, the contamination 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 relative size of the economy, therefore, 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 allows an aggregation over nearly the whole world.

Following Galí (1999), we consider a VAR model on the growth rates of average labor productivity (APL) Δz_t^h and hours worked Δh_t (and also total employment Δn_t for a robustness check) to evaluate the response of labor input to permanent technology shocks. Unlike Galí (1999), we define labor

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

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 group between advanced and developing countries. 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 also plots 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.

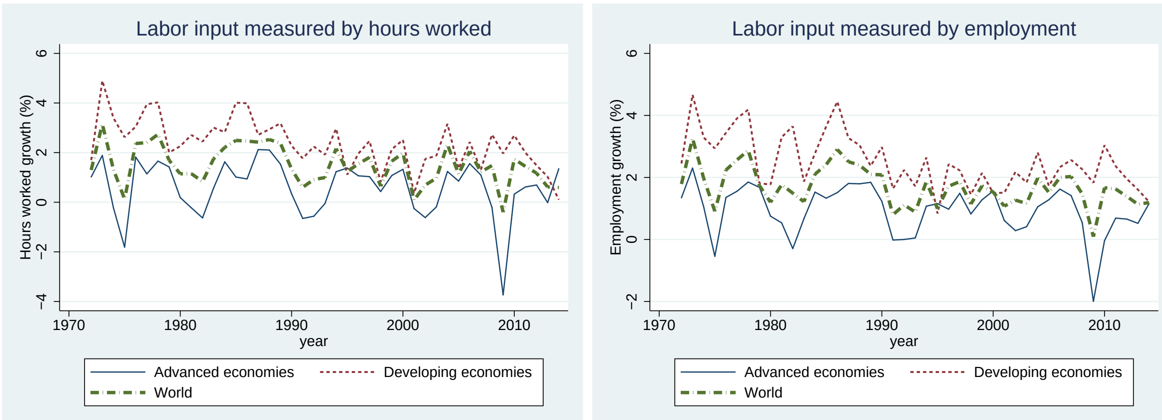
3.1 Identification of Technology Shocks

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

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.

model admits a VMA(∞) representation $Y_t = C(L)u_t$, where $C(L) = (I_2 - B_1L - ... - B_pL_p)^{-1}$ 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 Augmented Dickey Fuller (ADF) tests for unit root in labor input. For each group of economies, we regress the growth rate of aggregate employment on a constant, lagged levels and lags of the first differences. The results of ADF test with 2 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.[11]

Table 3.1: ADF unit root tests 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 an ADF test with 2 lags, an intercept (and a time trend for log-level data). Sample period 1970-2014.

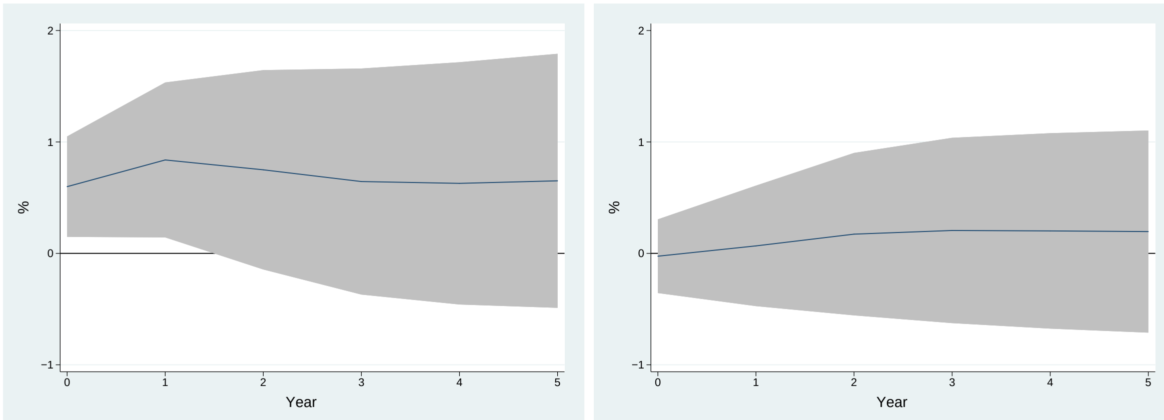
3.2 Baseline Results

We first report the results using the aggregate measure of technology shocks and the aggregated labor input as suggested by Dupaigne and Fève (2009). For each group of countries, we report the impulse response function (IRF) of total aggregated hours worked to a permanent world technology shock and its centered 90% confidence interval obtained by standard bootstrap techniques, using 500 draws from the sample residuals. Figure 3.3 displays the estimated responses of aggregated hours worked to the world permanent productivity shock. 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 1970. In this exercise, hours worked is aggregated over a balanced panel of 27 advanced and 16 developing economies, respectively. The left panel shows the response of hours worked of the advanced economy group and the right panel shows the response of hours worked of the developing economy group.

So far we have assumed that both groups of advanced and developing economies are subject to the identical world productivity shock. If each individual economy is fully integrated to the rest of the world, such as the analysis of the G7 countries in Dupaigne and Fève (2009), it could be considered as a reasonable assumption. However, our analysis contains a sample of developing economies where the

[11] For a country-by-country case in the robustness check section, we also conduct ADF tests 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.

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



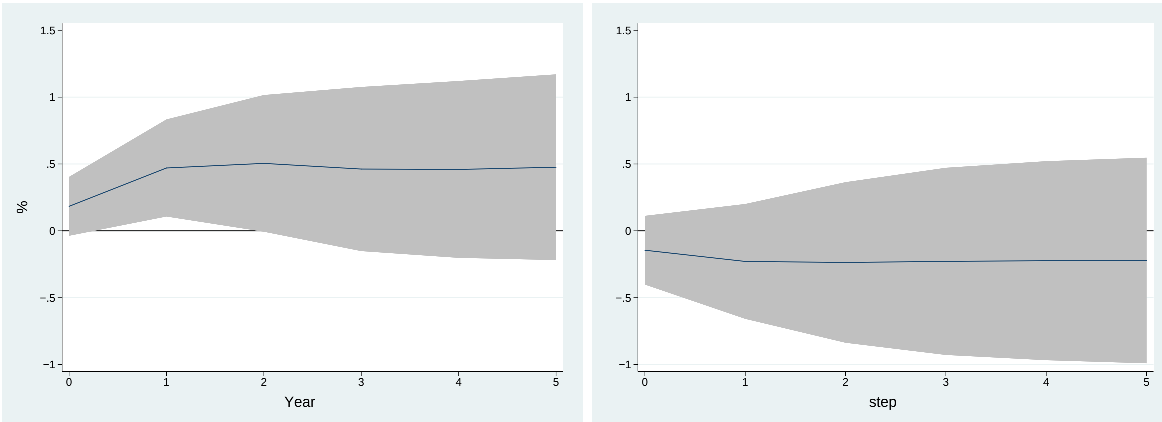
Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{World,h}, \Delta h_t^{Advanced}$) in the left panel and developing economies ($\Delta z_t^{World,h}, \Delta h_t^{Developing}$)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

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 permanent technology shocks by using the ratio of the real output aggregated over each group to the same measure of aggregated hours worked in the previous exercise, under the working assumption that technology spillover occurs mainly among countries with a similar income-level or economic development. 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 frontiers, 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

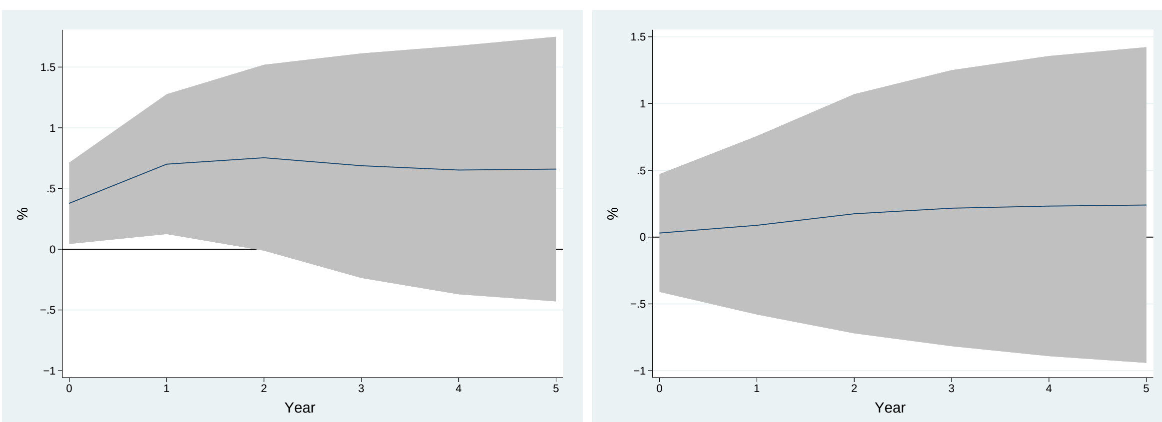
Figure 3.4: IRF of hours worked to the group-specific permanent technology shock



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.

group of advanced economies and this finding hardly changes when using the group-specific technology shock (Figure 3.6).[12]

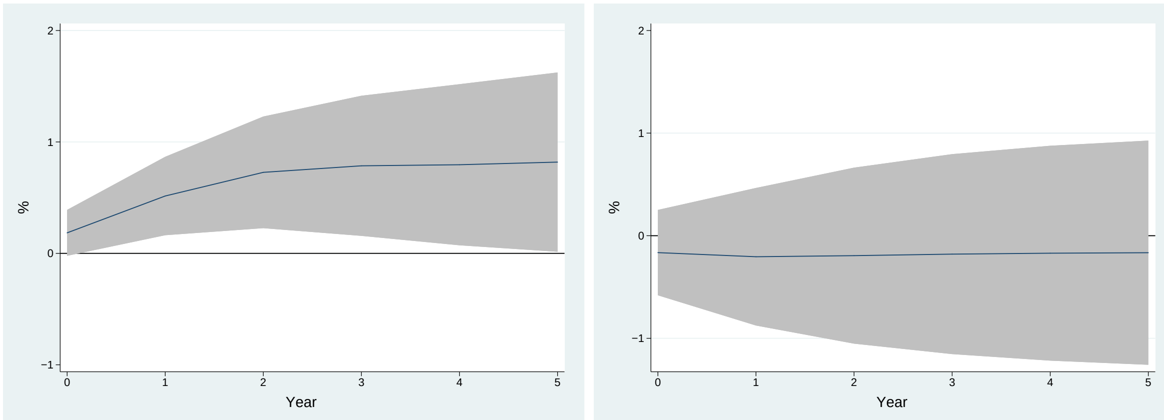
Figure 3.5: IRF of total employment to the world permanent technology shock



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.

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

Figure 3.6: IRF of total employment to the group-specific permanent technology shock



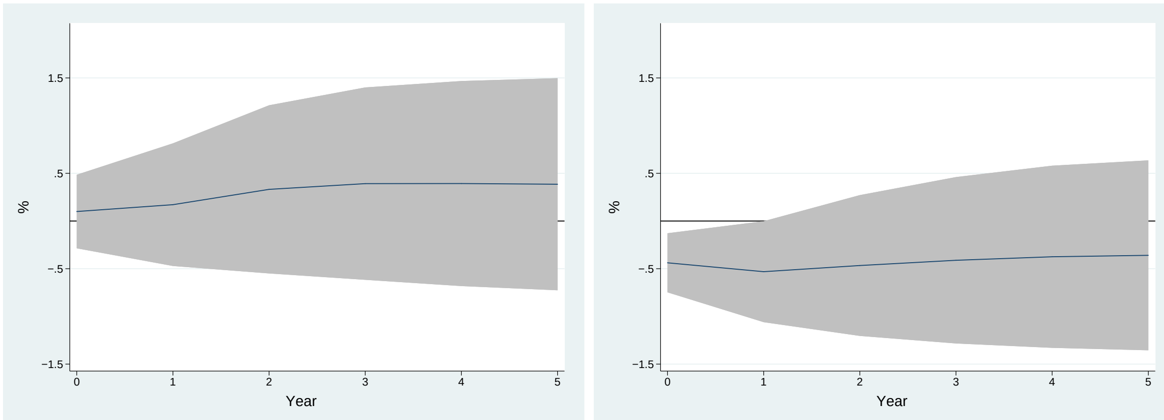
Note: This figure displays the impulse response function of total employment to the permanent group-specific technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{Advanced,n}, \Delta n_t^{Advanced}$) in the left panel and developing economies ($\Delta z_t^{Developing,n}, \Delta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

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 zeros in the developing economy group. Thus we repeat our analysis after dropping a set of low-income countries. 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. Thus 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.

In addition to trade globalization since the far 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. Thus we repeat our analysis using the sample from 1985 only and find that the responses

Figure 3.7: IRF of hours worked to the permanent technology shock in developing economies: without LICs (left) and using advanced economy technology shock instead (right)



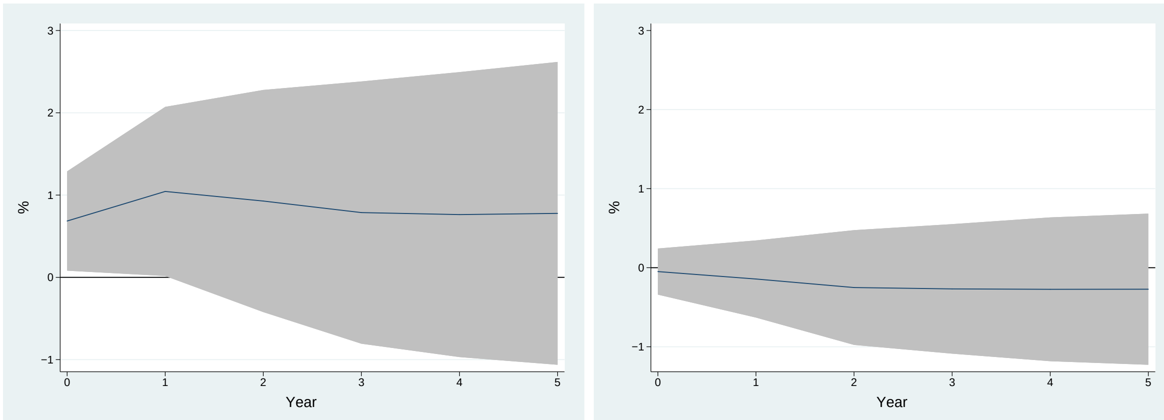
Note: This figure displays the impulse response function of hours worked to a permanent world technology shock in a bivariate VAR model of emerging economies without low-income countries ($\Delta z_t^{World,h}, \Delta h_t^{Emerging}$) in the left panel and the impulse response function of hours worked 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.

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.[13]

So far, we have used only 43 countries in the analysis since historical data on hours worked are only available in these countries. However, 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 much more countries (31 advanced economies and 72 developing economies), thereby mitigate this concern. As shown in Figure 3.9, both the qualitative and quantitative differences in the response of employment to the permanent world technology shock still remain when using a substantially larger sample of 103 countries.[14]

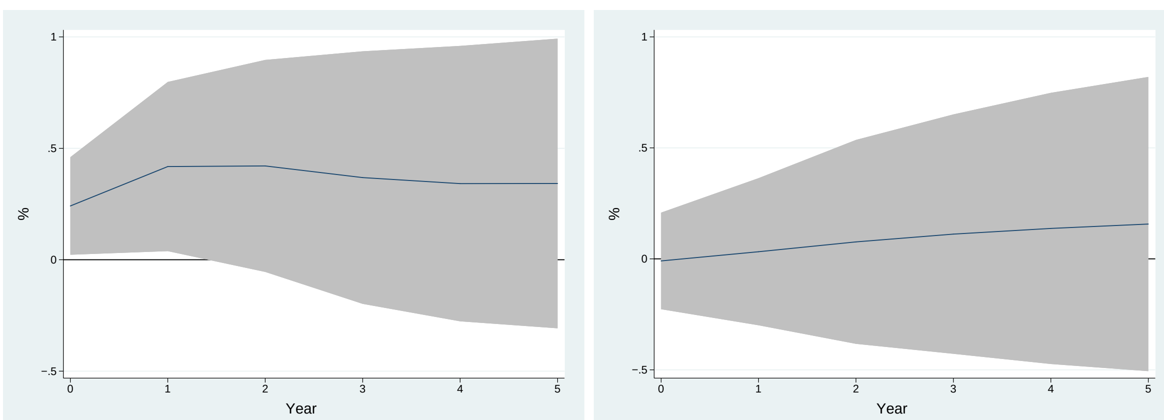
[13]We also conduct the same set of robustness checks using total employment as a labor input and find similar results.
[14]Our results also hold when using a smaller sample of emerging market economies (47 countries) after dropping low-income countries, which might be subject to the data quality concern.

Figure 3.8: 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 3.9: IRF of total employment to the world permanent technology shock using the full sample



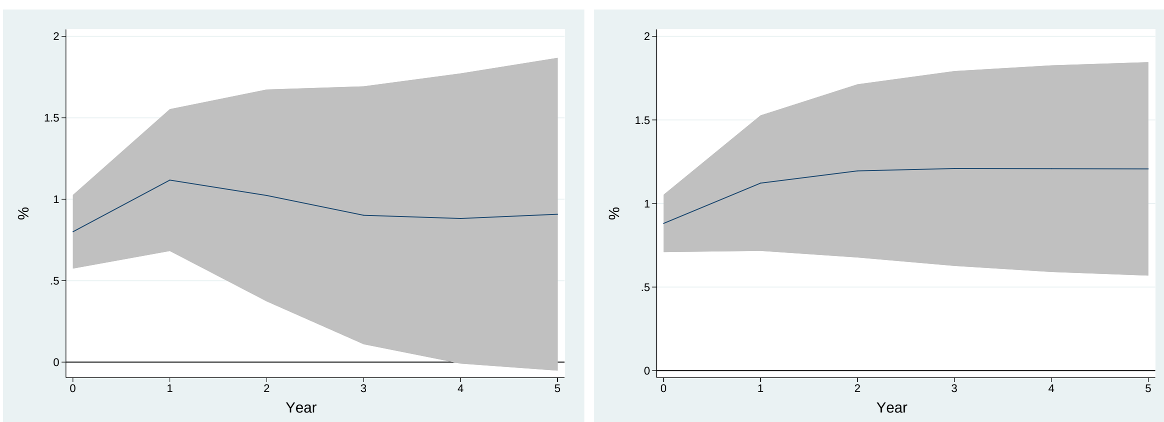
Note: This figure displays the impulse response function of total employment to a permanent world technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{World,n}, \Delta n_t^{Advanced}$) in the left panel and developing economies ($\Delta n_t^{World,n}, \Delta n_t^{Developing}$)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

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 business cycle properties. Thus we plot 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 3.10 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 two groups of countries, suggesting that the conditional response to the technology shock plays an important role in understanding the distinct feature of business cycles and labor market dynamics in developing 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.

Figure 3.10: 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.

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 Figure 3.10, 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 cycles 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

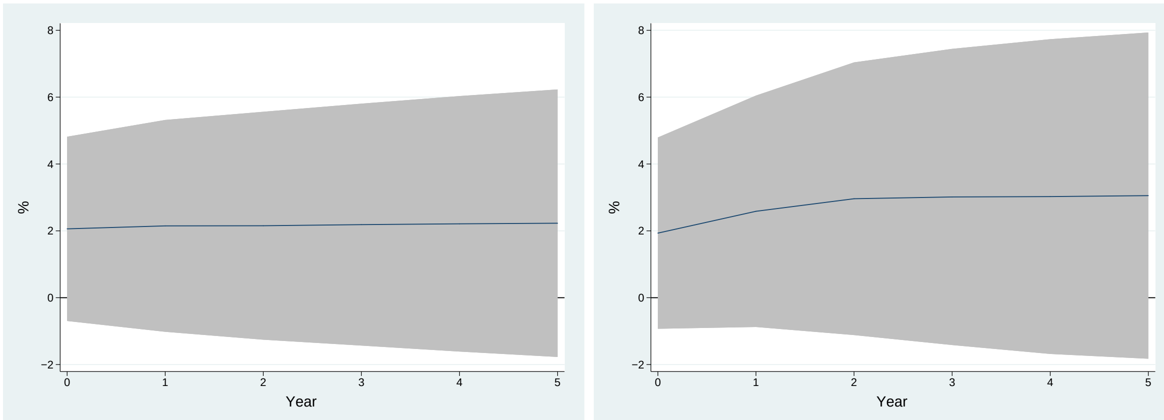
Note: Because there are only two structural shocks, the non-technology shock accounts for the rest of the variation. "Baseline" indicates the forecast error variance decomposition from the baseline specification. "Group technology" indicates the forecast error variance decomposition from the specification 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 used a parsimonious bivariate VAR model with labor productivity and labor input variables to study potential heterogeneity in the response of labor input to the technology shock. This is because the primary focus of the paper is to understand distinguished labor market dynamics in developing economies from those in advanced economies over business cycles. 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 $A_{12}(1) = A_{13}(1) = A_{23}(1) = 0$. Under this long-run restriction, we identify the technology shock only and do not separately identify other structural shocks in the system. Given that we are only interested in the response of labor and consumption to the technology shock, further identification of the other structural shocks is not necessary.

Figure 3.11 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. 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 in these economies.

Figure 3.11: 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.

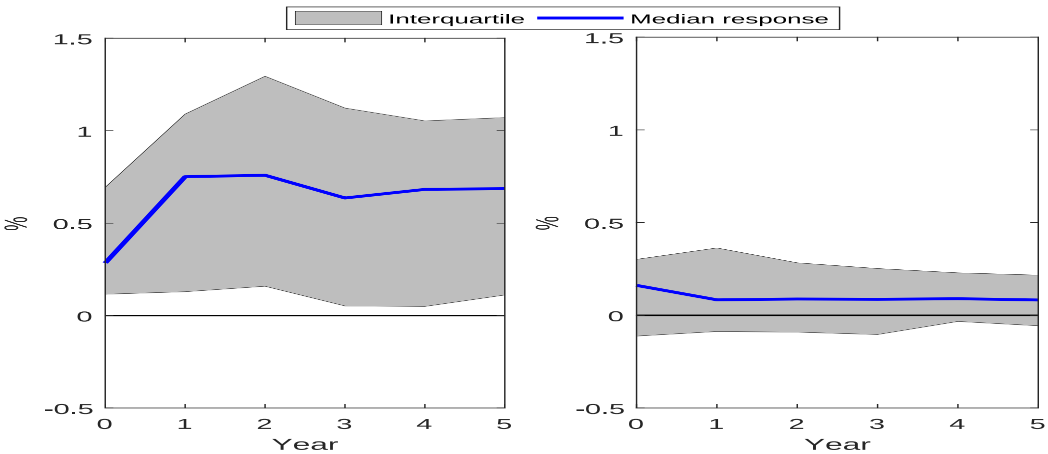
3.5 Country-by-Country Analysis

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 3.12 shows the case of hours worked and Figure 3.13 shows the case of employment. In both cases, it is clear that the response of labor input is much larger in advanced economies compared to developing economies, confirming the results using aggregate-level labor input.[15]

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 3.14 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

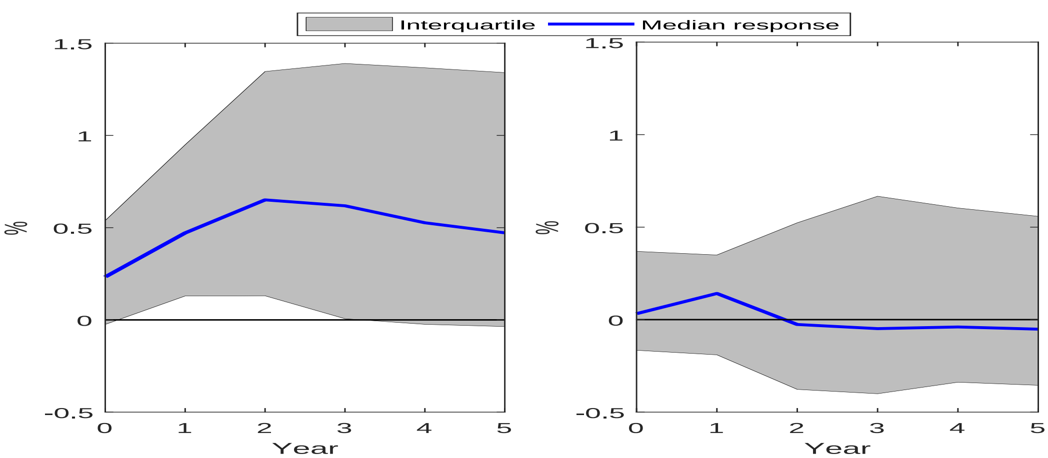
[15]The pattern of the response of employment hardly changes when extending the sample to include all 103 countries. The results are available upon request.

Figure 3.12: 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.

Figure 3.13: Country-by-country IRF of employment to the world permanent technology shock: advanced vs. developing economies

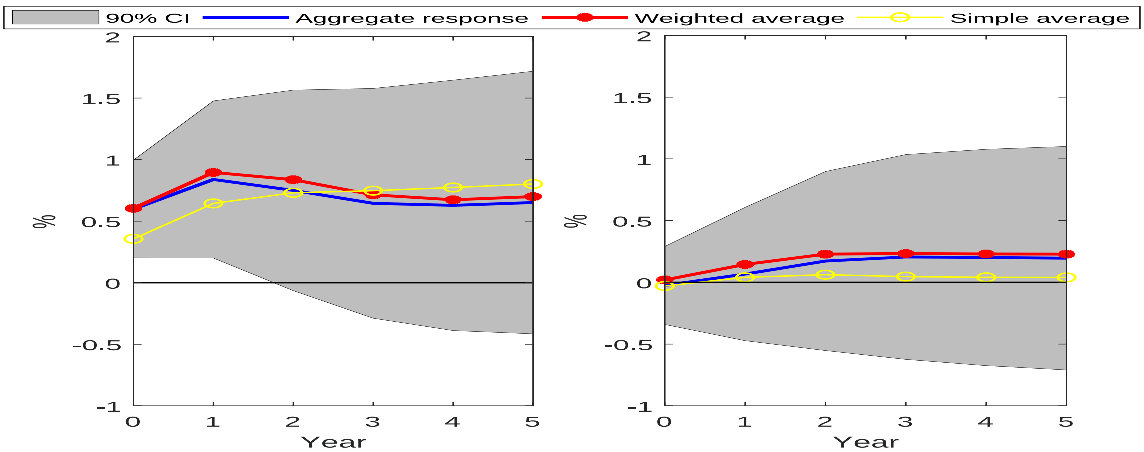


Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model $(\Delta z_t^{World,n}, \Delta n_{i,t})$. The left panel shows the interquartile distribution of advanced economies and the right panel shows the interquartile distribution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

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 further 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. Because a

Figure 3.14: 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.

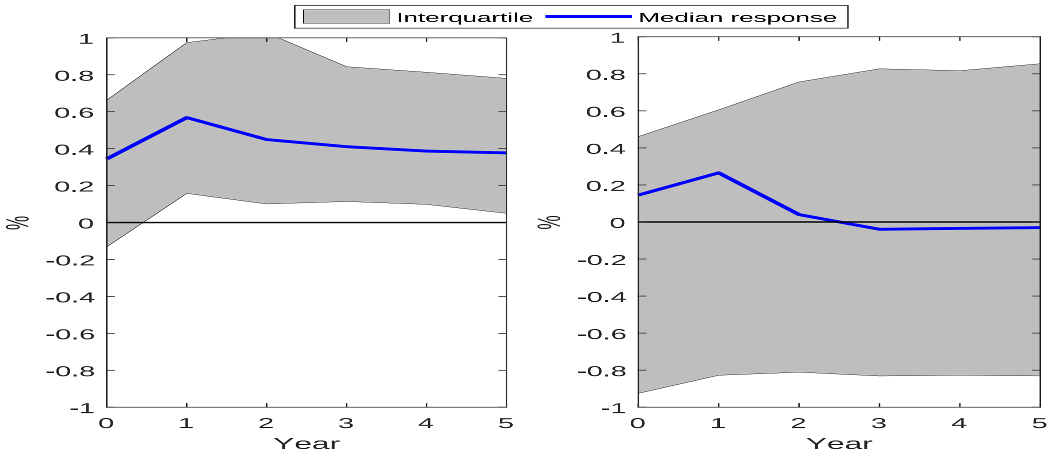
single stochastic trend hits permanently the country-level labor productivity, the labor productivity differentials help capture persistent country-specific components in labor productivity. As shown in Figure 3.15, the response of hours worked in the three-variable VAR model is similar to those obtained with the two-variable VAR model. If anything, the addition of productivity differentials in the VAR slightly shifts down the responses of labor input for both groups.

4 RBC Model Augmented with Subsistence Consumption

Thus far, 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.

Importantly, our empirical findings cast doubt on the common use of GHH preferences to explain distinct business cycle properties of developing economies. GHH preferences have been adopted in many small open economy models (Correia, Neves, and Rebelo (1995), Neumeyer and Perri (2005), and Garcia-Cicco, Pancrazi, and Uribe (2010), among others) to generate the countercyclical behavior of

Figure 3.15: 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.

the trade balance-to-output and avoid the case where hours worked falls in response to a rise in trend productivity due to wealth effect. However, the muted response of hours worked and employment to the positive technology shock in our structural VAR model suggests that the wealth effect is indeed important in developing economies. We discuss briefly why the adoption of alternative preferences cannot explain jointly the set of empirical stylized facts.

Adoption of alternative preferences. In a class of standard RBC models with KPR preferences (King, Plosser, and Rebelo (1988)), income and substitution effects of the increase in real wages driven by a positive productivity shock cancel out each other. Since 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. Our finding regarding the response of hours worked to the technology shock in developing economies suggests that GHH preferences are not an appropriate description of the representative household in developing economies.

Instead, Jaimovich and Rebelo (2009) develop a utility function (the JR preferences) that allows to parameterize the strength of short-run wealth effects on the labor supply, thereby encompassing 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.

Thus in Jaimovich and Rebelo (2009)'s model, 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 also dampens the response of consumption, which is difficult to be reconciled with higher consumption volatility in developing economies. Overall, varying the parameter γ cannot match two salient features of developing economy business cycles (relative volatility of consumption and labor) simultaneously.[16]

Li (2011) conducts this kind of analysis by varying the parameter γ.[17] 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 behaviors in developing economies. Lastly, varying the parameter γ alone cannot explain the difference in steady-state behaviors of hours worked documented in Bick, Fuchs-Schündeln, and Lagakos (2018).

[16]Of course, assuming different structural parameters in the preferences across countries is not the best approach to explain cross-country differences in the business cycle properties.

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

4.1 Empirical Relevance of Income-level and Subsistence Consumption

Then what is the plausible mechanism that explains our empirical finding? To answer this question, we highlight that a poverty line over per-capita income is significantly different across countries, suggesting its role in explaining the cross-country difference found in the earlier section. 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.

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.

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 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, resulting in a consistent measure of the average level of subsistence consumption during the sample period. The correlation is 0.26 and it is statistically significant at 1%. Moreover, the right hand panel in Figure 4.1 shows a strong negative correlation 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.[18]

Of course, we do not argue that the subsistence consumption is the only channel accounting for different labor market (and consumption) dynamics between advance and developing economies. Other structural factors might also account for the stylized facts in Table 2.1. Thus we test whether the

[18]The correlation is -0.39 and statistically significant at 1%

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.

following three candidate factors can explaining the stylized facts: (i) trade openness, (ii) labor market regulations, (iii) the size of the informal economy. First, trade openness is a plausible factor in explaining different labor market dynamics between advanced and developing countries because it governs the degree of technological spillover. Second, heavier labor market regulations can reduce the response of labor input to the technology shock mechanically if everything else equal. Lastly, the size of informal economy may mask the heterogeneity in the relative volatility of labor input to output.

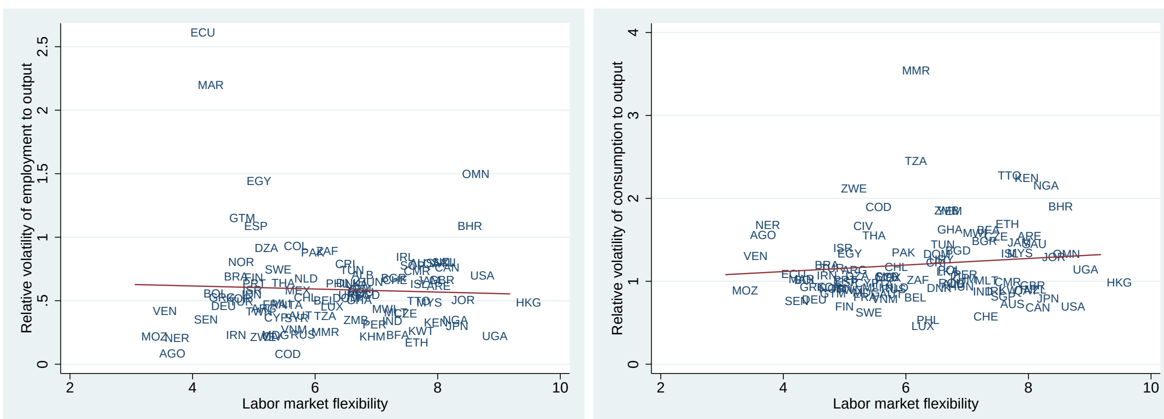
We use the most basic measure of trade openness that is the ratio of exports plus imports to GDP and take the average of this value from 1970 to 2014. To capture institutional differences in labor markets across countries, we use the labor market regulation index is taken from the Fraser Institutes Economic 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 the widely used index by Schneider, Buehn, and Montenegro (2010) to measure the size of the informal economy.

We plot the correlation between relative volatility of employment and consumption to output with the 1970-2014 average of the three structural factors. Figure 4.2-4.4 show that these alternative factors fail to explain the patterns about the relative volatility of labor input and consumption to output simultaneously. Although the size of the informal economy is strongly correlated with the relative volatility of consumption, it is not correlated with that of employment.

Figure 4.2: Trade openness and the relative volatility of employment and consumption to output

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.

Figure 4.3: Labor market regulations and the relative volatility of employment and consumption to output



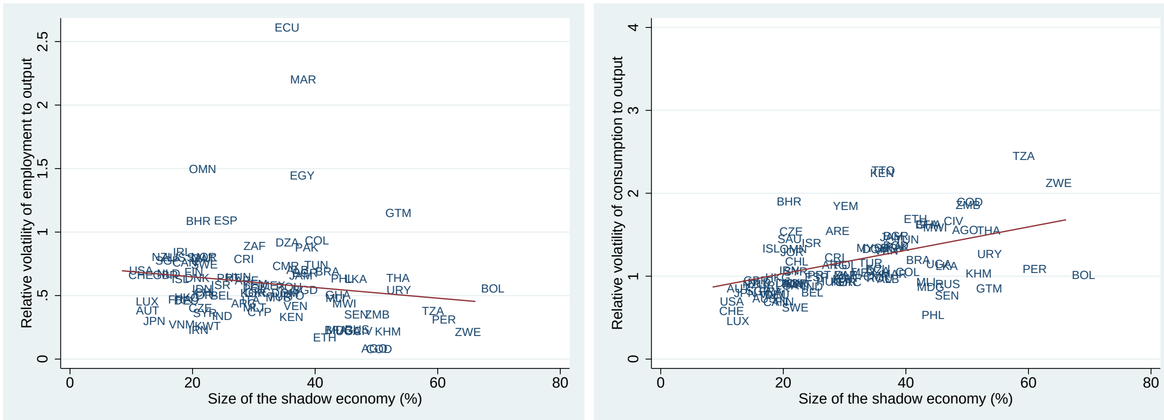
Note: This figure displays the correlation between the average degree of labor market regulations from 1970 to 2014 and the relative volatility of employment and consumption to output.

We test the correlation suggested in Figure 4.1 - 4.4, 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 and X_i is a vector of the four structural factors suggested above for a country i. We first include the average GDP per capita in X_i then add each of the rest three structural factors in turn. Finally, we include the all

Figure 4.4: Size of the informal economy and the relative volatility of employment and consumption to output



Note: This figure displays the correlation between the average size of the informal economy as a share of GDP from 1970 to 2014 and the relative volatility of employment and consumption to output.

four factors together.

While we do not claim causality, it is clear from Table 4.2 and 4.3 that the level of average PPP-adjusted income, or equivalently, the level of subsistence consumption is the most important factor in explaining simultaneously cross-country differences in the relative volatility of employment to output and that of consumption.

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

	(I)	(II)	(III)	(IV)	(V)
GDP per capita	0.078***	0.089***	0.083***	0.068**	0.071**
	(0.020)	(0.020)	(0.018)	(0.029)	(0.032)
Trade openness		-0.001			-0.001
		(0.001)			(0.001
Labor market regulations			-0.027		-0.032
			(0.035)		(0.043)
Informal economy				0.000	-0.001
				(0.003)	(0.003)
Constant	-0.132	-0.181	-0.015	-0.027	0.219
	(0.194)	(0.189)	(0.298)	(0.329)	(0.552)
N	102	101	98	93	93
r2	0.068	0.077	0.079	0.048	0.069

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

As already illustrated, the size of the response of hours worked to a technology shock depends on the relative size between a substitution and an income effect. As Bick, Fuchs-Schündeln, and Lagakos

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

	(I)	(II)	(III)	(IV)	(V)
GDP per capita	-0.149***	-0.152***	-0.170***	-0.052	-0.046
	(0.042)	(0.040)	(0.042)	(0.045)	(0.042)
Trade openness		0.000			0.000
		(0.001)			(0.001
Labor market regulations			0.071**		0.080***
			(0.029))		(0.029)
Informal economy				0.011**	0.014***
				(0.004)	(0.004)
Constant	2.587***	2.596***	2.340***	1.327**	0.683
	(0.411)	(0.401)	(0.426)	(0.509)	(0.531)
N	102	101	98	93	93
r2	0.154	0.154	0.212	0.232	0.304

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

(2018) point out, the role of subsistence consumption in determining the size of income effect becomes smaller as actual consumption level rises. In other words, the income effect becomes lower in high-income economies as subsistence consumption becomes less binding, which implies that subsistence consumption can be a plausible candidate to explain our empirical finding without changing parameters in the household utility function directly. Moreover, Ohanian, Raffo, and Rogerson (2008) find that the standard growth model appended to include taxes and a modest subsistence consumption effect performs well 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, further suggesting the important role played by subsistence consumption in explaining behaviors of hours worked.

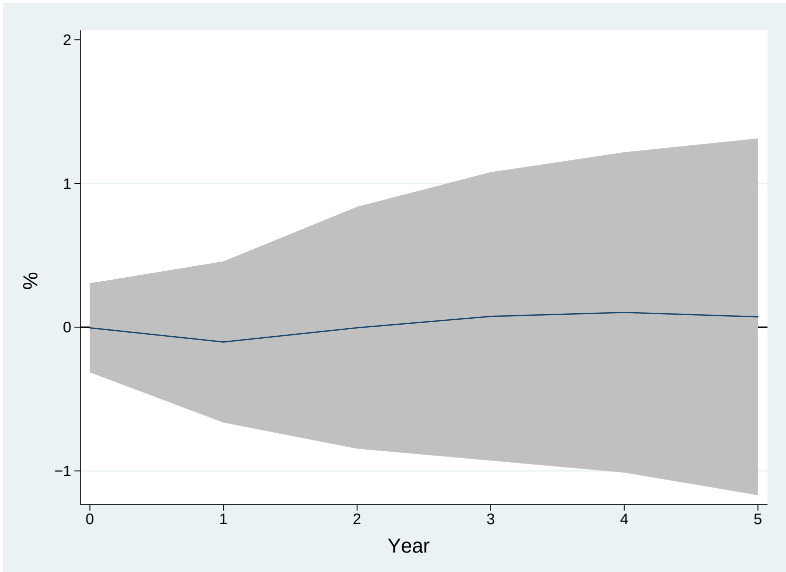
One might argue that the subsistence consumption channel is irrelevant for middle-income countries anymore and these countries are the one mostly studied in the emerging market business cycle literature. However, Ohanian, Raffo, and Rogerson (2008) show that the subsistence channel is important for even a high-income country like Japan in the earlier period. Moreover, most of studies on emerging market economies focus the period since 1990 due to the data availability, mainly on interest rates.[19] Given that many of middle-income emerging market economies were quite poor until 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

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

to 1970. As shown in Figure 4.5, 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 4.5: 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.

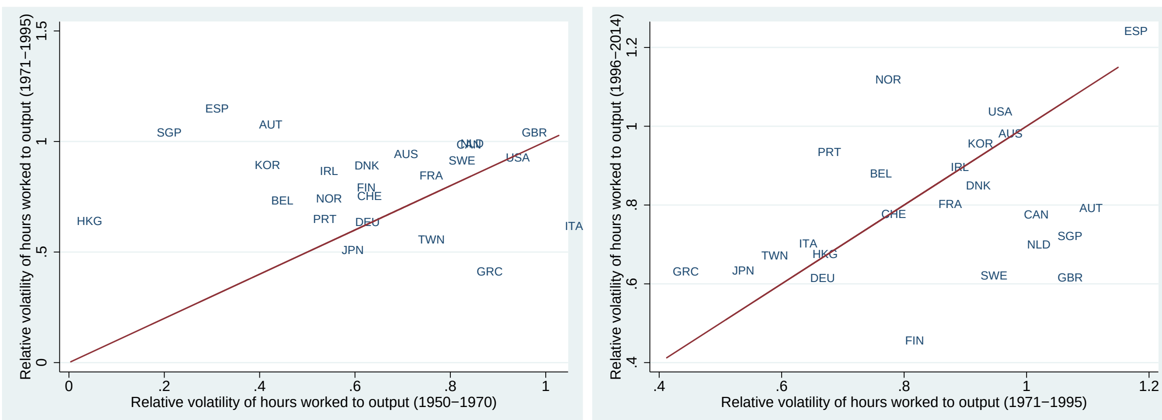
Moreover, we show that the relative volatility of hours worked to output—one of the key business cycle properties distinguishing high-income and low-income countries—also increases over time in advanced economies.[20] The left panel in Figure 4.6 compares the relative volatility of hours worked to output 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.

It is still possible that the increase in the relative volatility of hours worked to output is a secular phenomenon that is nothing to do with subsistence consumption. However, the right panel in Figure 4.6

[20] While most of 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.

shows that it is unlikely the case. 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 (the relative volatility of hours worked to output decreases in a half of the advanced countries).[21] Such an interesting pattern found in time-series data supports the idea that subsistence consumption is key to understanding the distinct business cycle properties of developing economies.

Figure 4.6: 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).

In the following section, we check whether our simple extension of the RBC model augmented with 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 will 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 that helps obtain the intuition of the key mechanism. Consider a consumer utility maximization problem:

[21] 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.

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

subject to a resource constraint $c = Zh$ where $\bar{c} \geq 0$ is subsistence consumption and $Z > 0$ denotes TFP. We assume that $\sigma < 1$.

Solution of 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 usual RBC model. Then under the assumption that $\sigma < 1$, hours worked increases unambiguously as TFP increases, which is the main prediction of the RBC type 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 lower response of hours worked to TFP shock? The important channel, which we call as a 'subsistence consumption' channel, is captured by the equation (4.6): h^* becomes higher as $\bar{c}$ increases. This 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 $\bar{c}$. Suppose that Z increases. As workers supply a lot of labor already, she cannot increase her supply of labor as much as she wants even when productivity is high. On the contrary, although a decrease in Z 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 generalized subsistence consumption-augmented RBC model. We consider a social planner's problem given as follows:

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

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 period 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 total factor productivity, 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 in order for our model to exhibit balanced growth property (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 analysis.[22]

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

Predictions of the model. We first test if the behavior of our model is consistent with the stylized facts observed in developing economies. Figure 4.7 plots impulse response functions of labor input to one-time-one-unit shock to technology. If subsistence consumption is zero, the model economy collapses

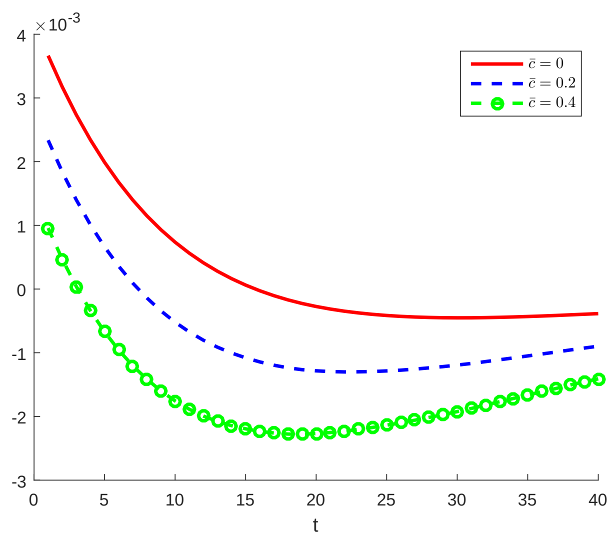
[22]Note that $c_t = \tilde{c}_t + \bar{c}$ implies $\sigma(c_t) = \sigma(\tilde{c}_t)$ as $\bar{c}$ is constant.

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

to a standard RBC economy. Therefore, it is natural to observe a positive response of hours worked to the technology shock, which is the usual prediction of the RBC model (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 is able to reproduce our novel empirical finding and also consistent with Bick, Fuchs-Schündeln, and Lagakos (2018) who find a positive relationship between the income-level and country-specific hours-wage elasticity estimated from individual data.[23] The intuition is discussed below.

Figure 4.7: Response of hours worked to a technology shock: Model prediction



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

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. Compared to advanced economies, developing countries 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))

Figure 4.8 plots the relationship between variables of interest and the subsistence consumption to income ratio. In particular, we vary $\bar{c}/y$ from zero (corresponding to an advanced economy) to 0.5 (corresponding to a low-income country). The solid red line in Figure 4.8a shows that steady-state hours worked is increasing in subsistence consumption, which is consistent with Bick, Fuchs-Schündeln, and Lagakos (2018)'s finding. 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. The results are in line with Boz, Durdu, and Li (2015)'s finding: hours worked become less volatile in developing economies. Moreover, they replicate the empirical regularity found in Figure 4.1 and 4.2 successfully.

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 respond less to changes in real wage; see Figure 4.9). Thus with steeper labor supply curve, (1) hours volatility declines but (2) wage volatility increases as the subsistence consumption level rises. Thus the response in the green dotted line can 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: Dynamics of the model economy

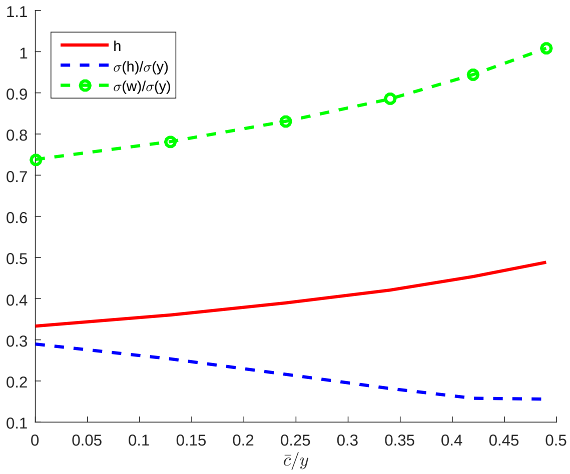


Figure 4.8a: Labor market behaviors

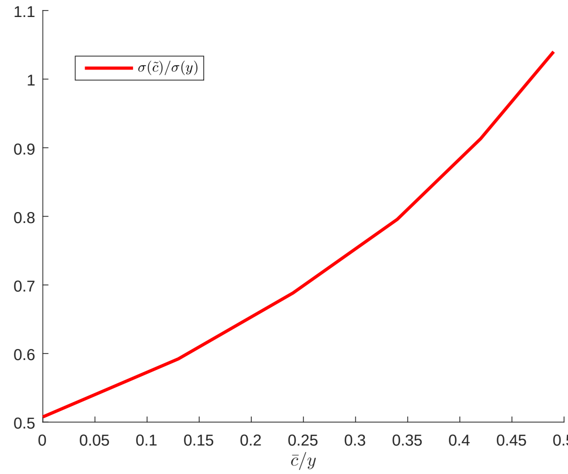


Figure 4.8b: Relative volatility of consumption

5 Can Alternative Models Explain Our Findings?

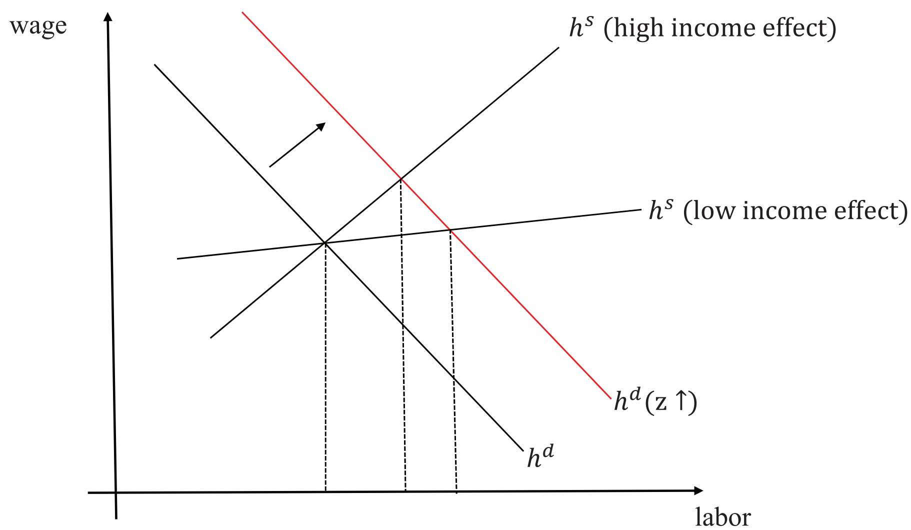
We have provided a minimal departure from a standard RBC model, which explains well the salient feature of consumption and labor market dynamics in developing economies. While this approach is not necessarily the unique way to explain the data, we review alternative models briefly and test whether they can explain the set of empirical stylized facts. We do not necessarily discuss every element of each model here for brevity of the paper.

5.1 New Keynesian Model with Nominal Price Rigidities

The first natural candidate to explain our finding is the degree of price rigidities. The negative response of hours worked to the permanent technology shock in Galí (1999) advocates the new Keynesian model with nominal price rigidities. Thus one might argue that prices are more rigid in less-developed economies for whatever reasons, resulting in the smaller response of hours worked to a permanent technology shock in these economies.

To test this hypothesis, we consider a canonical three-equations New-Keynesian model in Galí (2008) that 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 5.1a plots the IRFs of hours worked

Figure 4.9: Description of the labor market



to a 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 hours worked is greater in these economies (Bick, Fuchs-Schündeln, and Lagakos (2018)). 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

Figure 5.1: Response of hours worked to a technology shock: Existing theories

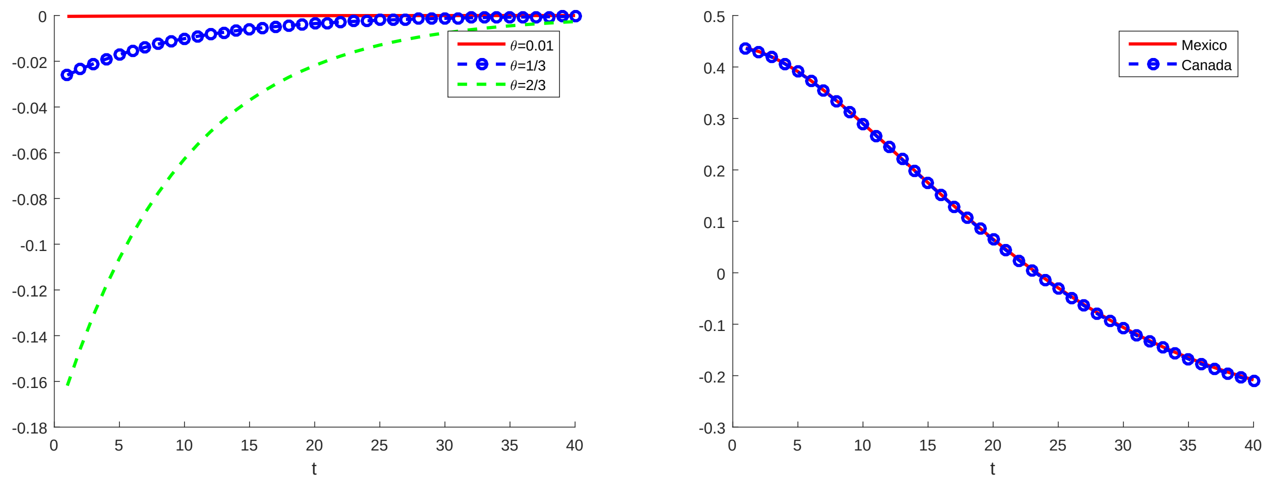


Figure 5.1a: New-Keynesian Model

Figure 5.1b: Aguiar and Gopinath (2007) Model

Calvo parameter, but instead a function of a markup at the steady-state.[24]

5.2 Model with Trend Growth Shocks

A strand of literature has introduced alternative shocks, such as a shock to trend growth (Aguiar and Gopinath (2007) among others) and a shock to interest rates (Neumeyer and Perri (2005) among others) to explain the observation that business cycle properties of emerging (and developing) economies are different from those of advanced economies.

In this section, we discuss whether these classes of models can explain our finding. Especially we test whether the model by Aguiar and Gopinath (2007) can generate a set of the stylized facts we find. 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, 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 regime switches observed in emerging market economies. We consider transitory productivity shock in the exercise so that results are comparable with other computational exercises.[25]

[24] 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. Results are available upon request.

[25] Even when we interpret a growth trend shock as a permanent technology shock in the structural VAR analysis in the previous section and consider the response of hours worked to the permanent technology shock, the result is identical.

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 5.1b.[26] It is clear that the current model, which introduces an alternative shock to generate a simulated economy that resembles a typical small-open developing economy (Mexico) and small-open advanced economy (Canada), cannot generate lower response of hours worked in emerging economy. Intuition is simple; their success relies on the introduction of additional shocks to reproduce observed second moments (and (auto-) correlations). Thus the labor market structure is (i) exactly equivalent to the usual RBC type model and (ii) identical between the two economies (Canada and Mexico) so that the response of hours worked to the technology shock should be also identical.

5.3 Model with Financial Frictions

Another possibility is that developing economies are subject to tighter financial constraints than advanced economies, thereby limit the labor choice of economic agents in developing economies. Indeed, a large body of the literature has emphasized the role of financial constraints 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.[27]

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's consider the following simplified borrowing constraints for the entrepreneur (producer of this economy) to get an intuition:

$$l_t^e \leq \gamma^H \mathbb{E}_t \frac{P_{t+1}^e H_t}{r_{t+1}} + \gamma^K K_t - \gamma^N (w_t^s N_t^s + w_t^b N_t^b), \tag{5.1}$$

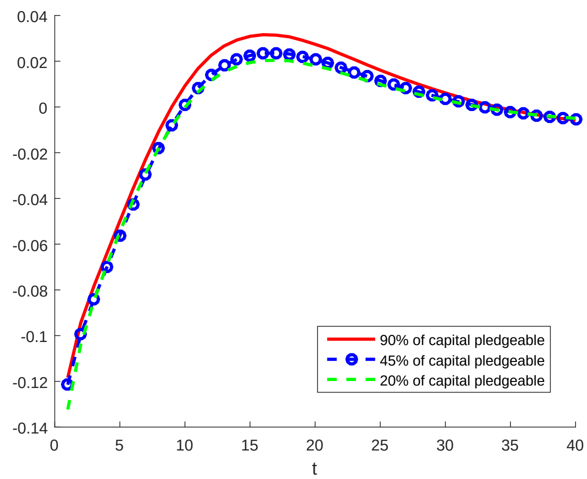
where l_t^e denotes loan made by the entrepreneur, γ^H, $\gamma^K \in (0,1)$ are collateral constraint on housing (H_t) and physical capital (K_t) that the entrepreneur owns. $\gamma^N (w_t^s N_t^s + w_t^b N_t^b)$ means that a fraction (γ^N) of labor income should be paid in advance.

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

[27] In particular, we use the model extended by Mok and Shim (2017) that extends the original model of Iacoviello (2015) to incorporate price rigidities. As is discussed in Section 5.1, price rigidities do not alter the finding reported here hence our choice of model is innocuous to our purpose.

We vary γ^K to capture the degree of financial constraints.[28] 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 technology shock that we are interested in is presented in Figure 5.2:

Figure 5.2: Response of hours worked to the technology shock: Iacoviello (2015) model



Note that hours worked respond negatively in this model because we use the New-Keynesian version of 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 to be significant. The intuition is simple; 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 required to dampen the response of hours worked to the technology shock.

6 Conclusion

Applying a structural VAR model with long-run restrictions to the labor market data of both advanced and developing economies, we document a novel empirical finding; the response of hours worked (and employment) to a permanent technology shock is smaller in developing economies than advanced economies. Together with other business cycle properties of developing economies that the volatility of

[28]The result is robust to changes in γ^H to capture the degree of financial frictions so that the changes in financial friction directly affect household's decision.

hours worked (real wage) is smaller (greater) than that of advanced economies, our finding challenges the existing models of their business cycles. 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 via shutting down the income effect is clearly inconsistent with our finding.

We then suggest that 'subsistence consumption, whose importance is greater in less-developed economies is the key for 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 serves a first convenient tool to evaluate the role of subsistence consumption in explaining labor market dynamics in developing economies. Our model can be extended to incorporate other important features of these economies, such as financial frictions, thereby reproduce more realistic business cycle properties.

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Table .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.