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Labor Market Dynamics under Technology Shocks: The Role of Subsistence Consumption

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Abstract

This paper establishes new stylized facts about labor market dynamics in developing economies and proposes a simple theory to explain them. We first show that the response of hours worked and employment to a technology shock—identified by a structural VAR model with long-run restrictions—is smaller in developing economies than in advanced economies. We then present the evidence that the level of PPP-adjusted income per capita—a proxy for the importance of subsistence consumption—is strongly and robustly correlated with the relative variability of employment and consumption to output across countries, while other structural characteristics are not. We argue that an RBC model augmented with subsistence consumption can account for the several salient features of business cycle fluctuations in developing economies, including their distinct labor market dynamics under technology shocks.

JEL classification: E21; E32; F44; J20

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

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1 Introduction

While there have been extensive studies on the business cycle properties of developing economies, including higher variability in consumption relative to output, and countercyclical net exports and interest rates (see Neumeyer and Perri (2005) and Aguiar and Gopinath (2007) among others), study on the labor market dynamics of the developing economies has been rare.[1] One exception is Boz, Durdu, and Li (2015), who showed 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. This paper aims to fill this gap in the literature by focusing on the labor market dynamics under the technology shocks in developing economies.

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))—, has been extensively studied for the last two decades. To the best of our knowledge, however, there has been no counterpart study examining it in developing economies. Motivated by this observation, this paper examines the responses of hours worked and employment to the technology shock, using a structural Vector Autoregression (VAR) model with long-run restrictions, *à* la Blanchard and Quah (1989) and Galí (1999). We exploit a large international panel dataset including many developing economies over the last 45 years. We find robust evidence that the response of hours worked and employment to the identified technology shock is smaller in developing economies compared to advanced economies.

We then document a strong correlation between the level of PPP-adjusted income per capita (our proxy for subsistence consumption) and the business cycle properties of consumption and labor variables. In particular, we show that the relative volatility of hours worked (consumption) to output is smaller (larger) in developing economies where subsistence consumption is still important. Interestingly, other potential characteristics of developing economies, such as trade openness, labor market regulations, and financial depth, fail to explain the cross-country heterogeneity in the business cycle properties.

Motivated by the above stylized facts, we extend a canonical real business cycle (henceforth RBC) model by embedding subsistence consumption to the utility function. We find that the equilibrium properties of our model are fully consistent with the observed dynamics in developing economies. As

[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.

the subsistence level of consumption increases—the model economy begins resembling a less-developed country—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 wages 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 (Boppart and Krusell (2016); Bick, Fuchs-Schündeln, and Lagakos (2018)) is also obtained as an equilibrium outcome.

The 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 the labor demand curve out, the hours worked responds less in an economy with a high level of subsistence consumption. Moreover, workers must supply a high level of labor at the steady state to maintain consumption above the subsistence level. Thus, on the one hand, workers cannot supply more labor in response to a positive technology shock, as the 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 implies that hours worked becomes less volatile but real wages become more volatile. As a result, the response of consumption to the technology shock becomes larger than in the model without subsistence consumption to hold the labor market equilibrium condition.

Our findings also call for a rethinking of the widely used Greenwood-Hercowitz-Huffman (henceforth GHH) preferences by Greenwood, Hercowitz, and Huffman (1988) in the small open economy literature since a seminal work by Mendoza (1991). Many small open economy models have adopted GHH preferences (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 a situation in which the hours worked declines in response to an increase in productivity due to the wealth effect. However, with this type of preferences, the marginal rate of substitution between consumption and leisure becomes independent of the consumption decision, which eliminates the wealth effect, and labor supply decisions become independent of intertemporal considerations as a result. Since labor supply is fully responsive to current shocks, there is less room for wages to adjust, which contradicts the large relative (small) volatility of real wages (hours worked) to output in developing economies. In the appendix B, we show that alternative modeling approaches, such as a model with price rigidity or financial frictions, are unlikely to explain our findings and other salient properties of developing economy business cycles jointly.

Our main contribution to the literature is twofold. First, we provide a new stylized fact on the labor market dynamics of developing economies that technology shocks generate smaller responses in hours worked in developing economies than in developed economies. Second, to the best of our knowledge, this paper is the first attempt to explain the economic fluctuations in developing economies using the subsistence consumption both theoretically and empirically. Although the growth/development literature has shown that a growth model augmented with subsistence consumption can explain the differences in growth experience across countries (Steger (2000); Herrendorf, Rogerson, and Valentinyi (2014); Bick, Fuchs-Schündeln, and Lagakos (2018)), none of the previous studies has analyzed the business cycle properties in developing economies using subsistence consumption.[2]

The rest of this paper is organized as follows. We first introduce the data used for our empirical analysis in Section 2 and conduct an extensive empirical analysis based on structural VAR models in Section 3. Section 4 examines whether subsistence consumption is a plausible factor to explain our findings. Section 5 introduces the RBC model with subsistence consumption and demonstrates its empirical relevance. Section 6 concludes.

2 Data and stylized facts

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. Although using higher frequency data is ideal for discovering underlying labor market dynamics over business cycles, it substantially reduces both the cross-sectional and time-series coverage of the data, especially for developing economies since 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.[3]

[2] While Ravn, Schmitt-Grohe, and Uribe (2008) and Achury, Hubar, and Koulovatianos (2012) introduce subsistence consumption into the business cycle models, their analyses do not consider developing economies.

[3] In a previous version of this 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 both the intensive and extensive margin of

Labor productivity is defined as (i) output per hours worked (ratio of real output to total hours worked) and (ii) output per employed person (ratio of real output to persons employed). We acquire 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 the 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.[4]

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

Stylized facts about the unconditional moments. 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. All series are HP-filtered using a smoothing parameter of 100. Despite the relatively small sample size used in the baseline analysis, most of the business cycle properties are statistically different between the two groups.[5] Table A.1 in the appendix presents the full list of countries used in the robustness check using employment data.[6] 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)

labor and for consistency with earlier structural VAR analyses on advanced economies, such as Christiano, Eichenbaum, and Vigfusson (2004), Galí (2004), and Basu, Fernald, and Kimball (2006).

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

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

[6]All of our empirical results hardly change when we regroup some advanced economies into a developing economy category. For example, some east Asian industrial countries are now considered 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.

by employing a substantially larger sample.[7]

3 Empirical findings from a structural VAR model

3.1 Measurement of technology shocks

The stylized facts about the unconditional business cycle moments of developing economies documented in the previous section suggest a possibility that some frictions in their labor markets prevent adjusting labor input to exogenous shocks. We focus on the behavior of labor market variables in response to a technology shock and do not identify an exact source of non-technology shocks, 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 covering both advanced and developing economies.

Unlike Galí (1999) who studied 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. While it is possible to define a country-specific technology or productivity shock by simply dividing the real output of each economy by the total hours worked, this naive approach could bias the measurement of a technology shock to the extent that technology shocks spill over from one country to others. 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.[8] 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. Dupaigne and Fève (2009) also suggest that the labor productivity of G7 countries cointegrates and

[7] 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.

[8] 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
Mean test	0.03	0.26	0.00	0.00	0.00	0.41
Median test	0.01	0.13	0.00	0.01	0.00	0.52

Note: σ denotes the standard deviation of the variable and ρ denotes the correlation between the variables. All series are HP-filtered using a smoothing parameter of 100. h, n, c, and y denote hours worked, employment, consumption, and output, respectively. * denotes a country belonging to the low-income category. The last two rows report p-values of Student's t (for means) and Mann-Whitney (for medians) tests of equality of means and medians of advanced and developing economy statistics.

displays a single stochastic trend, which calls for caution when using such a naive approach.

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, in addition to 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.[9] The aggregation across countries offsets the country-level stationary shocks that contaminate country-level data, thus mitigating the identification problem.

Specifically, 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 of 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.

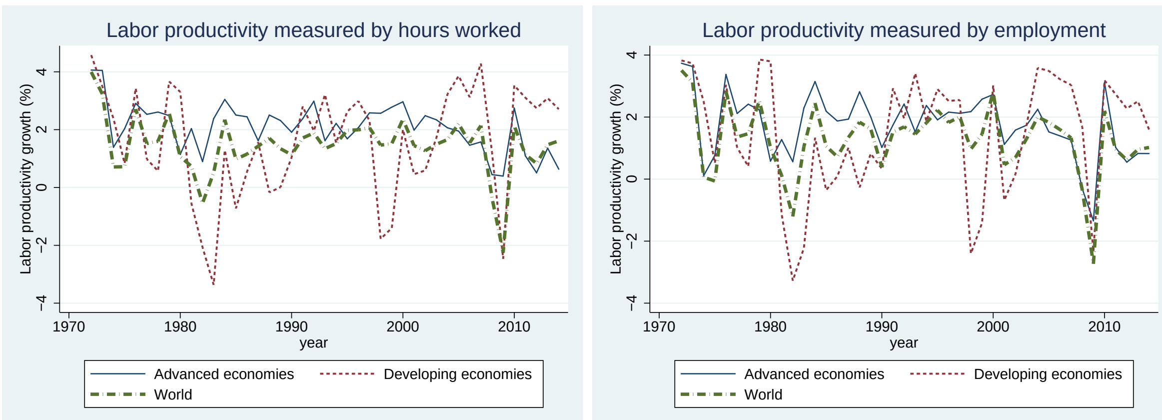
Based on the estimation of the data generated by the structural model, Dupaigne and Fève (2009) argue that a measure of labor productivity aggregated across countries improves the identification of the response of the labor input to a technology shock in the international context. Moreover, the contamination of country-level labor productivity by country-specific stationary shocks has two quantitative implications that are highly relevant for our purposes: (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 account for the bulk of world output.

Following Galí (1999), we consider a VAR model for 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), we define labor productivity as the ratio of real output aggregated over the countries in the sample to total hours

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

worked, which is also aggregated over the same sample. Figure 3.1 shows the so-called "world labor productivity" using hours worked (left panel) and employment (right panel) from 1970 to 2014. We also compute group-specific labor productivity, which is aggregated only for countries belonging to the same income group.

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 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.

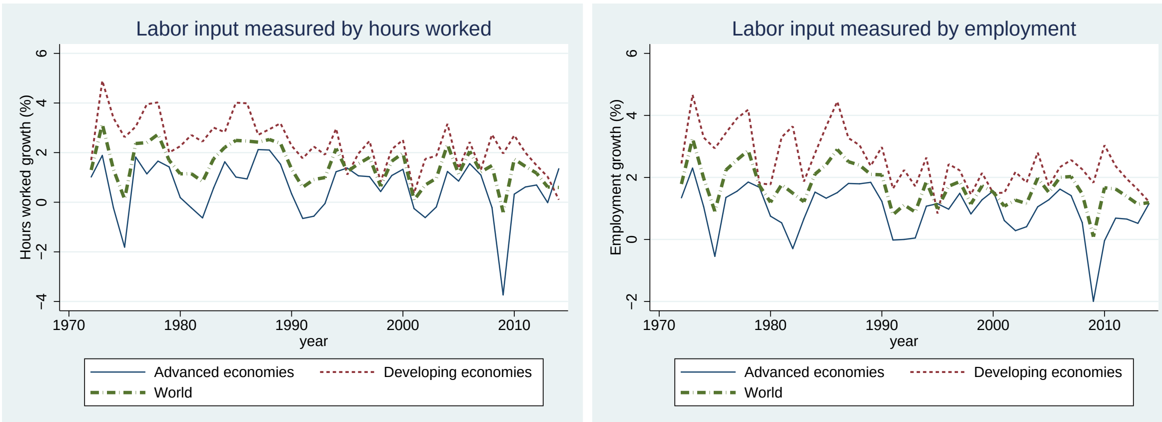
3.2 Baseline VAR model

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 the Akaike Information Criterion. Under usual conditions, this VAR model admits a VMA(∞) representation $Y_t = C(L)u_t$, where $C(L) = (I_2 - B_1 L - ... - B_p L_p)^{-1}$

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.

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., $A_{12}(1) = 0$. 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 for the G7 countries in Dupaigne and Fève (2009), the null hypothesis of the unit root cannot be rejected at conventional levels for the level of hours worked and employment, whereas it is clearly rejected for the first-differences at least at the 5% level, supporting the first-differences specification.[10]

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.

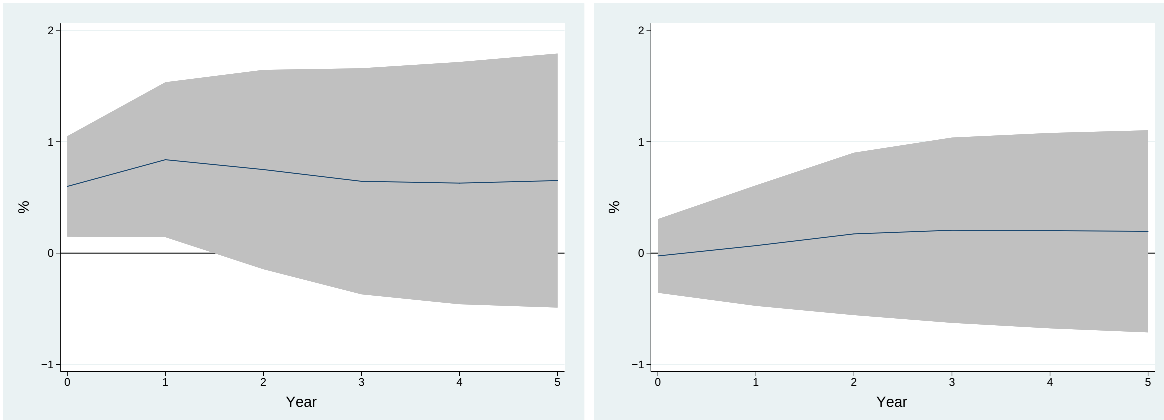
3.3 Main findings

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, world labor productivity is defined as the ratio of the world output using the PPP-adjusted real GDP to the sum of hours worked in 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. We use the PPP-adjusted GDP to take into account for differences in purchasing power across countries, which better approximates the 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 a one standard deviation shock to world productivity. We obtain a 90% confidence interval by standard bootstrap techniques, using 500 draws from the sample residuals. On the one hand, the 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

[10] For a country-by-country case in the robustness check section, we also conduct the ADF test for labor input in each individual country. In most countries, we find that the null hypothesis of the 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.

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 those in 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 simply driven by imprecise estimates.

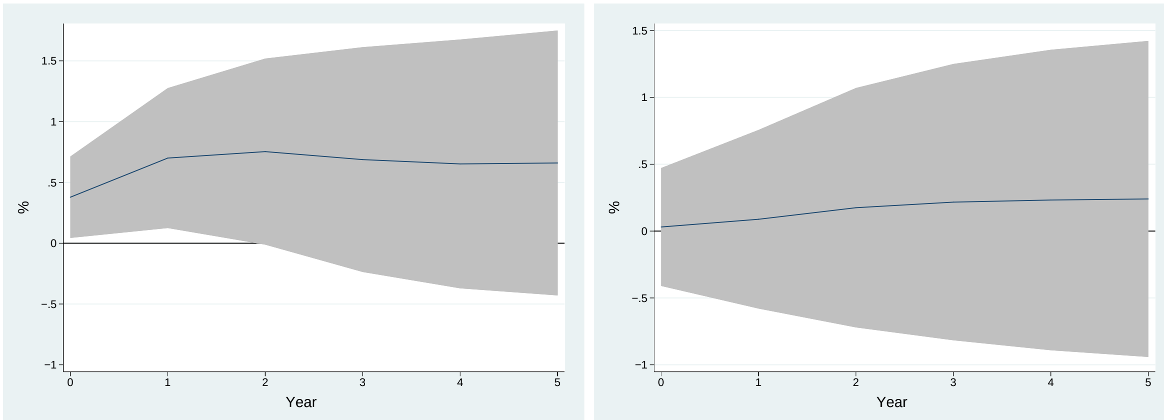
We repeat our analysis using an alternative measure of labor input (employment) and labor productivity. In this case, we define world labor productivity as the ratio of the real output of the world using the PPP-adjusted real GDP to the sum of total employment of the same 43 countries. When we estimate 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 3.4 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).[11]

3.4 Robustness checks

In this section, we provide the results from a battery of robustness checks. To save space, we only discuss the results here and move the relevant figures to the appendix A. First, we have assumed that

[11]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 between the two groups.

Figure 3.4: 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.

both groups of advanced and developing economies are subject to the identical world productivity process. To the extent that each individual economy is fully integrated with the rest of the world, it is a reasonable assumption for 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. Applying a dynamic factor model to a large number of countries, Kose, Otrok, and Whiteman (2003) also find that 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 output aggregated over each group to hours worked aggregated over the corresponding group, under the assumption that technology spillover occurs mainly among countries with a similar income-level. Figure A.1 in the appendix displays the results using group-specific technology shocks, suggesting that the smaller response of hours worked to the permanent technology shock in developing economies is not simply because the technology level of these countries is far from the world technology frontier, such as the U.S. This finding hardly changes when using employment instead (see Figure A.2 in the appendix).

Second, 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.3 in the appendix shows that our findings are not driven by the inclusion of LICs.

Third, 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 the so called "advanced economy technology shock." Since this modification affects only developing countries, we do not report the results for advanced economies. The right panel in Figure A.3 in the appendix confirms that the alternative measure of the technology process does not alter our conclusion.

Fourth, in addition to trade globalization that started in 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 (e.g., Prasad, Rogoff, Wei, and Kose (2007)). 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 significant trade and financial integration of the world economy. Thus, we repeat our analysis using only the sample from 1985. Figure A.4 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 it is unlikely the limited technology spillovers from advanced to developing economies are the cause for the muted response of labor input in developing economies.[12]

Fifth, we have used only 43 countries in the analysis as only these countries have sufficient time-series data on hours worked. However, our analysis does not necessarily span the entire world economy, resulting in potential bias in the measured world productivity. Data on total employment, however, are available in more countries, especially in developing economies (31 advanced economies and 72 developing economies). As shown in Figure A.5 in the appendix, both the qualitative and quantitative differences between advanced and developing economies in the response of employment to the permanent world technology shock, using a substantially larger sample of 103 countries, resemble the baseline

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

results.[13]

3.5 Additional VAR exercises

Thus far, we have only focused on the response of hours worked (or employment) to the technology shock identified from long-run restrictions. However, providing additional results helps understand the source of different properties of labor market dynamics and confirm the validity of our identification of structural shocks.

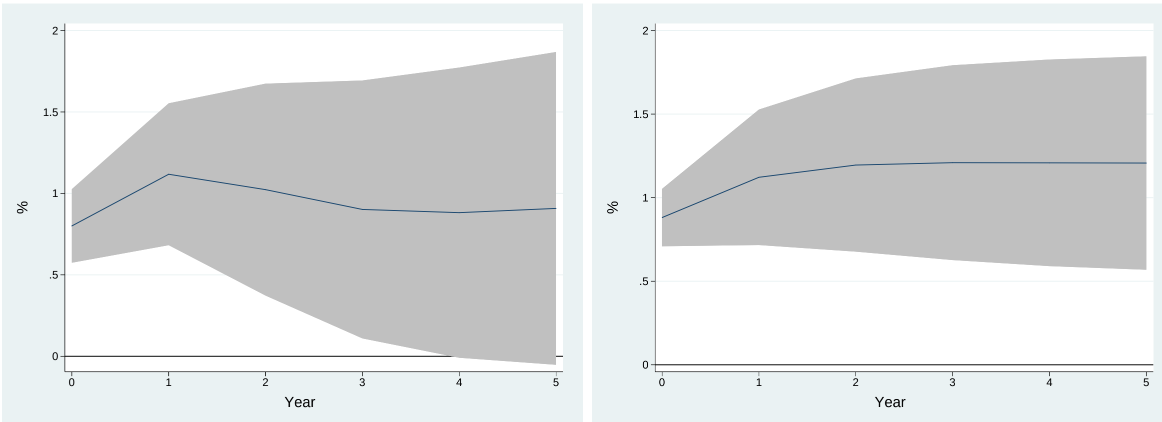
Response of hours worked to the non-technology shock. First, we estimate the response of labor input at the group level to the non-technology shock, which includes all kind of disturbances that do not have a long-run effect on world labor productivity. This exercise tests whether the response of labor input to the non-technology shock differs between advanced and developing economies. Figure 3.5 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, not the non-technology shock, plays an important role in understanding the distinct features of labor market dynamics in developing economies. This similar pattern is robust to (i) using a group-specific non-technology 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 Figure 3.5, 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.

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

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

Figure 3.5: 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.

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

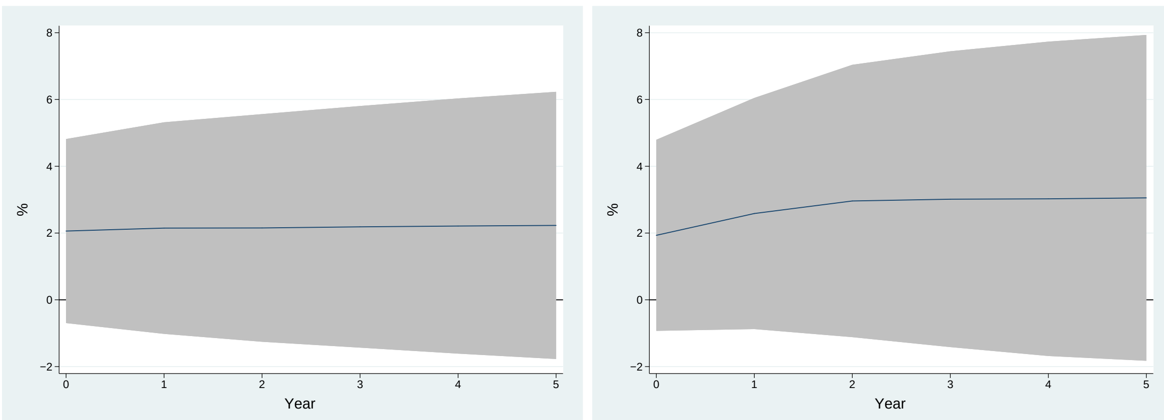
Note: Because there are only two structural shocks, the non-technology shock accounts for the rest of the variation. "Baseline" indicates the forecast error variance decomposition from the baseline specification. "Group technology" indicates the forecast error variance decomposition from the specification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

heterogeneity in the response of hours worked and employment to the technology shock, given our primary focus on distinguishing labor market dynamics in developing economies from those in advanced economies. Nevertheless, any sensible economic mechanism must explain another key feature of business cycle properties in developing economies simultaneously—the higher variability of consumption to output. To examine this issue, we 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 $A_{12}(1) = A_{13}(1) = A_{23}(1) = 0$.[14]

Figure 3.6 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 simply driven by larger measurement errors in the data from developing economies.

Figure 3.6: 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.

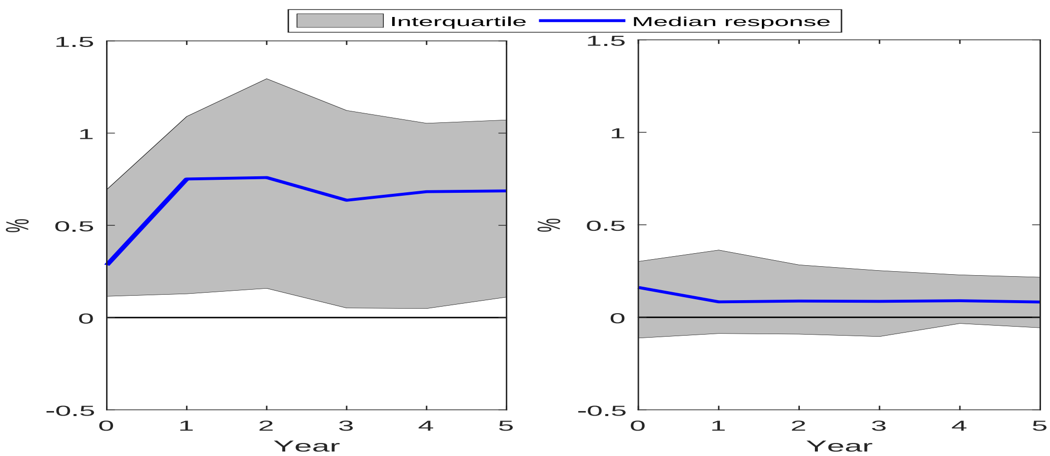
3.6 Country-by-country analysis

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

[14]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 order between hours worked and consumption in the VAR model above, keeping the same long-run restrictions.

to summarize the results. Figure 3.7 shows that of hours worked and Figure A.6 in the appendix shows the case of employment. In both cases, it is clear that the response of labor input is much larger in advanced economies than developing economies, confirming the results using the aggregate-level labor input.[15]

Figure 3.7: Country-by-country IRF of hours worked to the world permanent technology shock



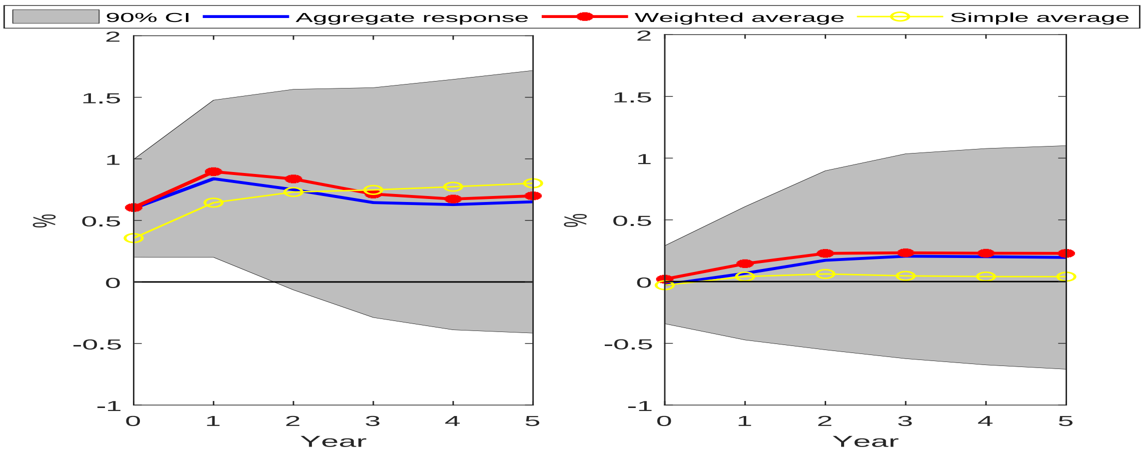
Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model $(\Delta z_t^{World,h}, \Delta h_{i,t})$. The left panel shows the interquartile distribution of advanced economies and the right panel shows the interquartile distribution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

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 3.8 compares this weighted response using country-level labor input with the previous response using aggregate-level labor input. We too 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 how 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 that 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

[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 3.8: 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.

Figure A.7 in the appendix, the response of hours worked in the trivariate VAR model is similar to those obtained with the bivariate VAR model. If anything, the addition of productivity differentials in the VAR slightly shifts the responses of labor input for both groups downward.

4 What explains a set of stylized facts?

How do we explain the set of stylized facts regarding both the unconditional and conditional business cycle moments documented in the previous section? The following six structural characteristics are well-known structural factors that can potentially explain the empirical findings: (i) trade openness, (ii) private credit provided by the banking sector (financial frictions), (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 forth in the literature as potential determinants of macroeconomic volatility, thereby providing a plausible explanation for our new empirical findings.

First, trade openness is a plausible factor in explaining different consumption and labor market dynamics because it is typically associated with a volatility of business cycles (Rodrik (1998)), and governs the degree of technological spillovers and the quantitative role of terms of trade shocks across countries (Kose, Prasad, and Terrones (2003)). Second, financial frictions have been studied extensively as a source of the 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 the higher relative volatility of consumption to output in developing economies by preventing efficient consumption smoothing (Özbilgin (2010); Naoussi and Tripier (2013)).[16] Third, the size of governments is also known to be correlated with output volatility (Rodrik (1998); Fatás and Mihov (2001)), which may affect the pattern of consumption and labor market dynamics. Fourth, we include a measure of institutional quality, which is also one of the most robust factors in 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 in 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 which its size can affect the relative volatility of consumption to output (Restrepo-Echavarria (2014); Shapiro (2015); Horvath (2018)).[17]

We measure trade openness by the ratio of exports plus imports to GDP as is standard in the literature. The degree of financial deepening is measured by the domestic credit provided by the banking sector as a percentage of GDP, which is also standard in the literature. We use the general government final consumption expenditure as 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 quality of institutions (a higher value indicates a better quality of institutions).[18] 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

[16] In a related study, Epstein and Shapiro (2019) find a negative and significant relationship between domestic financial development and unemployment volatility in developing economies.

[17] Shapiro (2015) finds that the relationship between the size of informal labor markets and unemployment volatility can be both positive and negative depending on the source of a change in the size.

[18] 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.

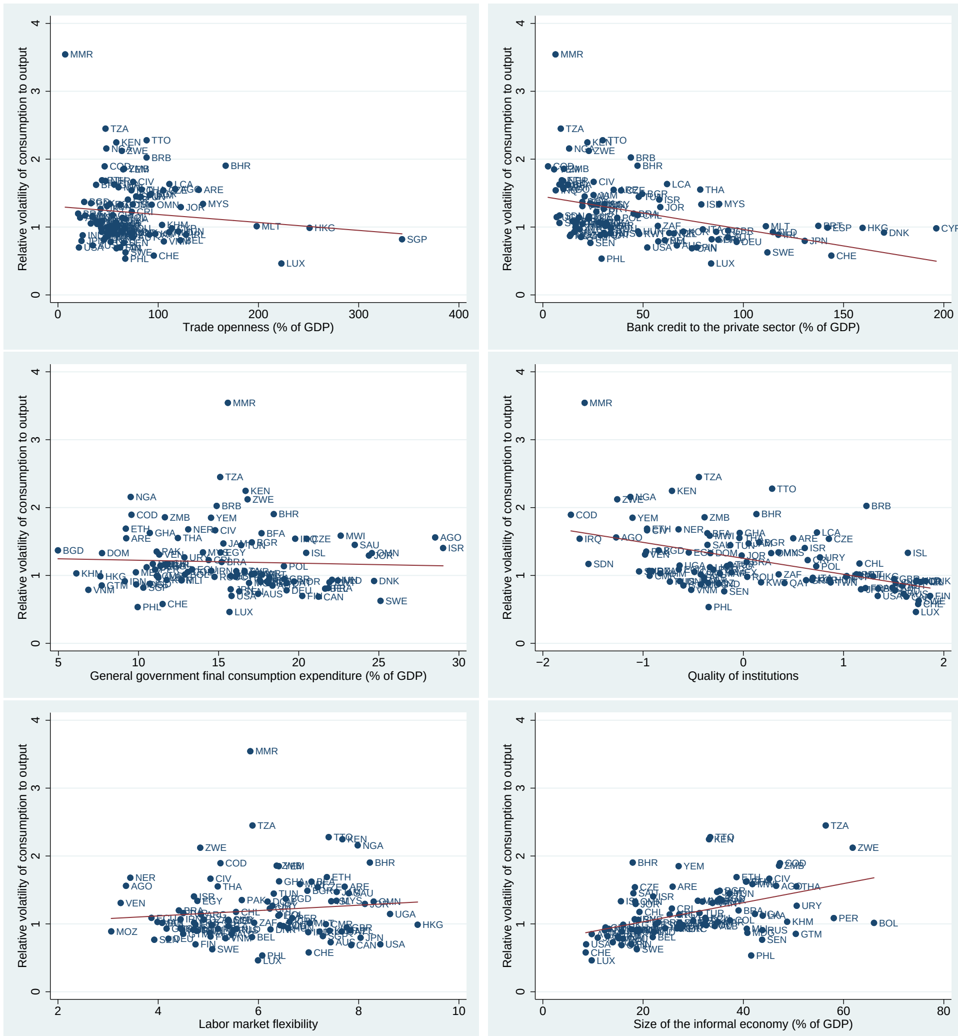
World (EFW) database, which is computed as the average of six subcategory indicators covering various aspects of labor market regulations, taking a value from 0 (low flexibility) to 10 (high flexibility). Lastly, we use the widely used index by Schneider, Buehn, and Montenegro (2010) to measure the size of the informal economy. When available, we use the average of each factor over the sample period between 1970 and 2014 in the following exercises.

We first test if above candidate factors employed in existing studies explain the distinct business cycle properties of developing economies that consumption volatility is larger while hours worked volatility is smaller in developing economies (Özbilgin (2010); Naoussi and Tripier (2013); Restrepo-Echavarria (2014)). We first plot the correlation between the relative volatility of consumption to output with the six structural characteristics in Figure 4.1 to check whether the relationship found in the literature holds in the broader sample of countries used in this study.

Consistent with the literature, Figure 4.1 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%. However, none of the other correlations is statistically significant at 10%. 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 4.2 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); however 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. While this is a crude test, which will be formally tested below, our simple analysis suggests that we need a third factor to explain the labor market dynamics in developing economies.

In addition to the aforementioned factors, we suggest that the level of subsistence consumption—proxied by a poverty line over PPP-adjusted per-capita income—is potentially an important factor. Although subsistence consumption is a widely-used concept, its precise meaning is often not properly stated (Sharif (1986)). Among many candidates, we proxy the level of subsistence consumption using the inverse of PPP-adjusted per capita income to maximize the sample size and ensure cross-country consistency. While we implicitly assume a common poverty line for countries in the sample, our mea-

Figure 4.1: Relative volatility of consumption to output and structural characteristics

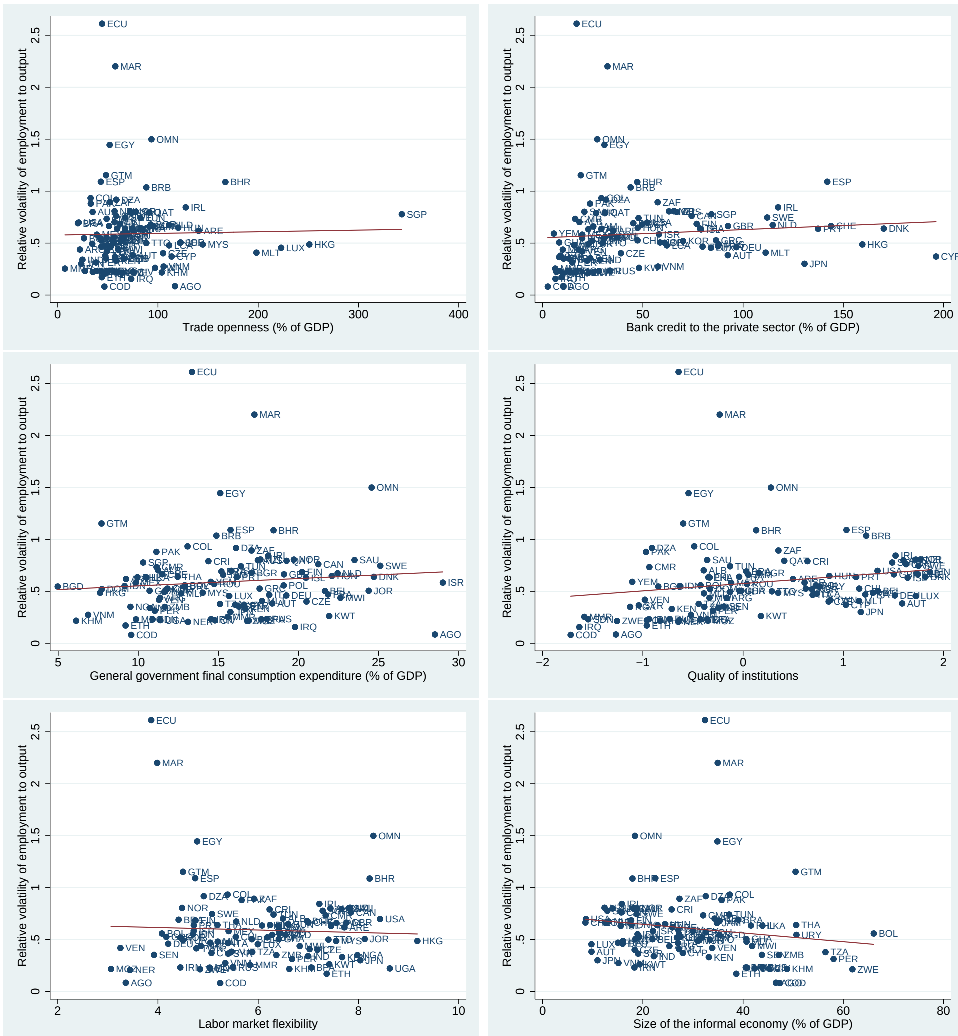


Note: This figure displays the correlations between the relative volatility of consumption to output and various structural characteristics.

sure can still approximate the relevance of subsistence consumption since per-capita income is adjusted by PPP, which accounts for heterogeneous purchasing power across countries. Table 4.1 shows that the subsistence consumption-income ratio 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 4.3 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. The correlation is

Figure 4.2: Relative volatility of employment to output and structural characteristics



Note: This figure displays the correlations between the relative volatility of employment to output and various structural characteristics.

0.26 and it is statistically significant at 1%.[19] Moreover, the right hand panel in Figure 4.3 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.

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

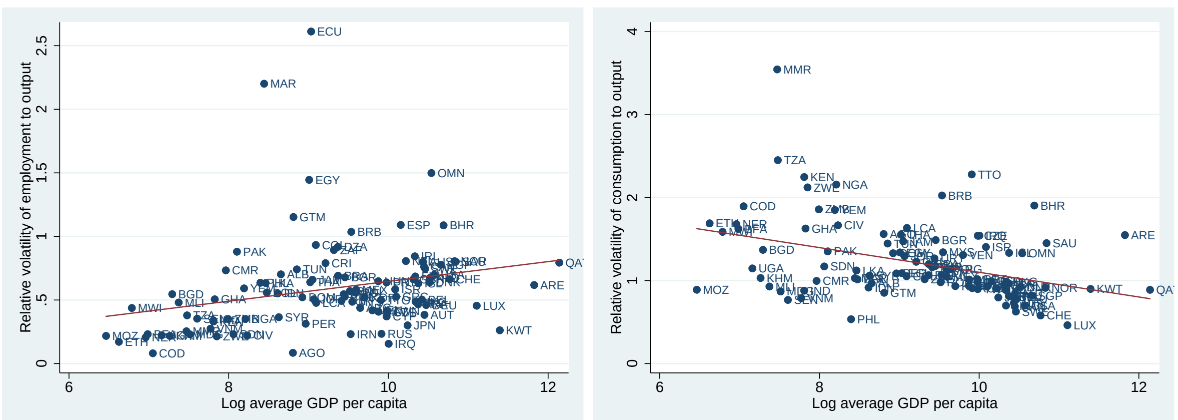
[19] Although Ecuador and Morocco seem outliers in terms of the relative volatility of employment to output, they do not drive our findings. Indeed, excluding these two countries from the sample strengthens the role of the income-level even more (the correlation becomes 0.44).

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.

Figure 4.3: 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 (left) and consumption (right) to output.

$$y_i = \alpha + \beta X_i + \epsilon_i, \tag{4.1}$$

where y_i is the relative volatility of employment (consumption) to output in country i over 1970-2014 and X_i is a vector of the seven structural factors for 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 six structural factors in turn. Finally, we include the seven factors altogether. Results are reported in Table 4.2 and Table 4.3.

It is clear from Table 4.2 and 4.3 that the level of average PPP-adjusted income per capita, or equivalently, the level of subsistence consumption is the most robust factor in jointly explaining the

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.

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.

cross-country differences in the relative volatility of employment and consumption to output. While this evidence supports the role of subsistence consumption in explaining the unconditional moments in labor market dynamics, this does not provide any evidence regarding the conditional moments (i.e., the response of labor input to the identified technology shock). Thus, we compare the size of the impact response of employment to the technology shock obtained from country-by-country VAR analysis in Section 3.6 to the level of subsistence consumption across countries. Figure 4.4 confirms that subsistence consumption also explains the cross-country heterogeneity in the response of hours worked (left panel) and employment (right panel) to the technology shock from structural VARs. The correlation is 0.28 and 0.25 and the associated p-value is 0.06 and 0.02, respectively.

Figure 4.4: GDP per capita and the impact response of hours worked and employment

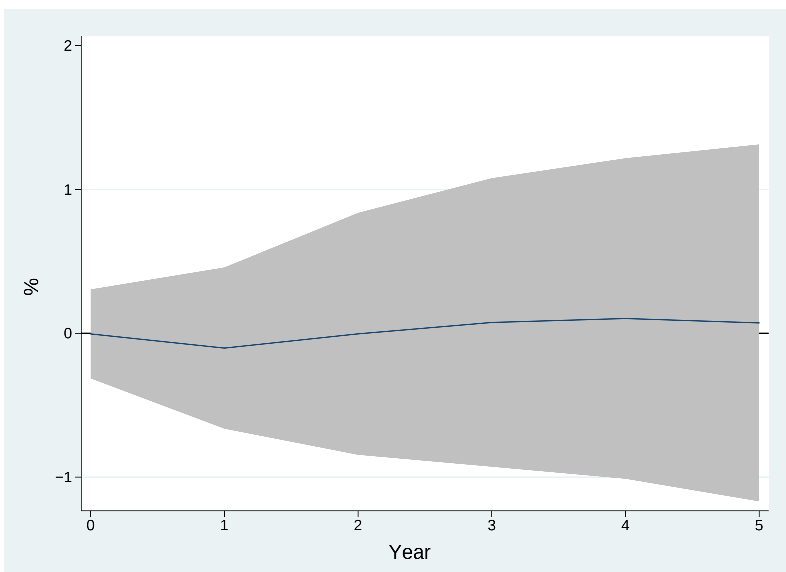
Note: This figure displays the correlation between the log of average income, measured by PPP-adjusted GDP per capita between 1970 and 2014, and the impact response of hours worked (left) and employment (right) to the identified technology shock in country-by-country VAR analysis in Section 3.6.

More evidence on the relevance of subsistence consumption. As already illustrated, the size of the response of hours worked to the technology shock depends on the relative size of the substitution and income effect. As Bick, Fuchs-Schündeln, and Lagakos (2018) note, the role of subsistence consumption in determining the size of the income effect becomes smaller as the actual consumption level rises. Boppart and Krusell (2016) also claims that the relative size of the income effect over the substitution effect on hours worked is key to understanding a trend decline in hours worked over a long period of time. Put differently, the income effect in high-income economies decreases as subsistence consumption becomes less binding, which implies that subsistence consumption can be a plausible candidate for explaining 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, in terms of both the overall changes in hours worked and the timing of the changes. Their findings suggest that subsistence consumption plays an important role 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 on the period since 1990 owing to limited data availability, mainly interest rates.[20] As many 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 4.5, 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 in advanced economies: 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 cycle properties distinguishing high-income countries from low-income countries—also increases over

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

time in advanced economies.[21] The left panel in Figure 4.6 compares the relative volatility of hours worked to output during 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 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 4.6 shows that once subsistence consumption becomes largely irrelevant for advanced economies after the 1970s, additional economic growth is not associated with an increase in the relative volatility of hours worked to output.[22] Though suggestive, such an interesting pattern found in the time-series data provides another support to the role of subsistence consumption in understanding the distinct business cycle properties of developing economies.[23]

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).

[21] 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.

[22] 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.

[23] See Boppart and Krusell (2016) for the consistent finding about changes in the average hours worked in advanced economies and the income effect over time.

5 RBC model augmented with subsistence consumption

We have newly established robust stylized facts about the response of hours worked and employment to the permanent technology shock. Combined with the distinct business cycle properties of 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 challenge 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 hours worked is mostly determined by changes in labor demand through productivity shocks. We illustrate how a minimal extension of adding subsistence consumption to the otherwise standard closed economy RBC model reconciles the set of empirical stylized facts documented in this paper.

5.1 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:

$$\max_{c,h} \frac{(c-\bar{c})^{1-\sigma}-1}{1-\sigma} - h \tag{5.1}$$

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.

The solution to the above model is given by

$$h^* = Z^{1/\sigma-1} + \frac{\bar{c}}{Z} \tag{5.2}$$

and $c^* = Zh^*$.

As we are interested in the response of hours worked to a technology shock, we differentiate the equation (5.2) with respect to Z:

$$\frac{dh^*}{dZ} = \frac{1-\sigma}{\sigma} Z^{1/\sigma-2} - \frac{\bar{c}}{Z^2} \tag{5.3}$$

Suppose that $\bar{c} = 0$, as in the standard RBC model. Under the assumption that $\sigma < 1$, the hours worked increase 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 the subsistence consumption-augmented model has potential to explain our main empirical finding.

Then, what is the underlying mechanism of the smaller response of hours worked to the technology shock in developing economies? The important channel, which we call a "subsistence consumption" channel, is captured by equation (5.3). h^* increases with $\bar{c}$, which is a natural consequence of introducing subsistence consumption. Workers should work more to keep their consumption level above the subsistence level. Thus, the disutility from working is higher in the economy with a higher level of subsistence consumption. Suppose that there is a positive technology shock hitting the economy. As a worker's pre-shock labor supply is high, she cannot further increase her supply of labor when productivity is higher. On the contrary, although a negative technology shock makes leisure more attractive, she cannot reduce her labor supply since she must maintain consumption above the subsistence level.

5.2 Main Model

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

$$\max_{c_t,k_{t+1},h_t} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\ln(c_t - \bar{c}) - \psi \frac{h_t^{1+\phi}}{1+\phi} \right], \tag{5.4}$$

subject to

$$c_t + k_{t+1} = Z_t k_t^{1-\alpha} h_t^{\alpha} + (1-\delta) k_t, \tag{5.5}$$

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:

$$\ln Z_t = \rho \ln Z_{t-1} + \varepsilon_t, \tag{5.6}$$

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

Subsistence consumption is incorporated in the utility function in a Stone-Geary form; log utility is considered to ensure the balanced growth path of our model (King, Plosser, and Rebelo (2002)). However, as shown by Li, Shim, and Wen (2017), using the 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.[24]

Calibrated parameter values are reported in Table 5.1. We note that our results do not depend much on the parameter values. In addition, we set ψ to ensure that the steady-state hours worked, h, is 1/3 when $\bar{c} = 0$.[25]

Table 5.1: 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

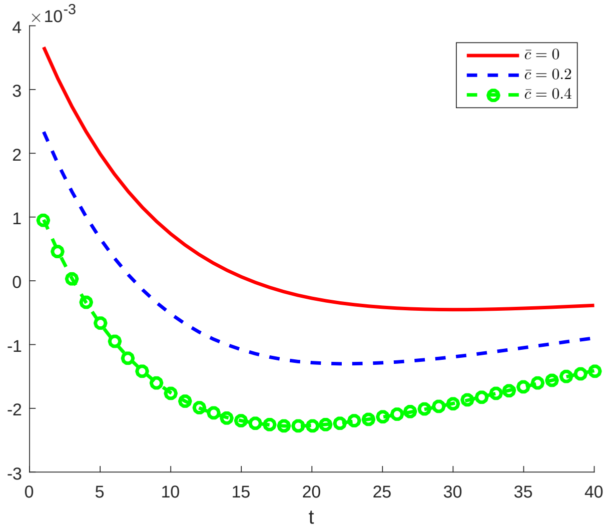
Predictions of the model. We first test if the behavior of our model is consistent with the stylized facts observed in developing economies. Figure 5.1 plots the impulse response functions of hours worked to one-time-one-unit shock to technology. If subsistence consumption is zero, the model economy 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 a high level of subsistence consumption respond less to the positive productivity shock. Thus, the RBC model with subsistence consumption can reproduce our novel empirical finding about the conditional moment of hours worked and employment. It is also consistent with Bick, Fuchs-Schündeln, and Lagakos (2018), who find a positive relationship between

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

[25] One might argue that habit formation, instead of the subsistence consumption, can explain our findings ($\ln(c_t - \alpha c_{t-1})$ with $\alpha > 0$ for instance). Under this assumption with external habit, it can be shown that higher hours worked in developing economies can be obtained with higher degree of habit formation (α). However, higher α implies lower consumption variations, which is inconsistent with the well-known fact that consumption volatility in developing economies is higher than in developed economies.

the income-level and hours-wage elasticity.[26]

Figure 5.1: Response of hours worked to the technology shock: model prediction



The 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 as countercyclical net exports and interest rates. Again, 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))

Figure 5.2 plots the relationship between the 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 5.2a shows that the steady-state hours worked

[26] 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.

is increasing in subsistence consumption, consistent with Boppart and Krusell (2016) and Bick, Fuchs-Schündeln, and Lagakos (2018). 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 wages to output vary with $\bar{c}/y$, respectively. They replicate the empirical regularity found in Figure 4.3 and 4.1 successfully and also corroborate the findings of Aguiar and Gopinath (2007) and Boz, Durdu, and Li (2015).

Figure 5.2: Dynamics of the model economy

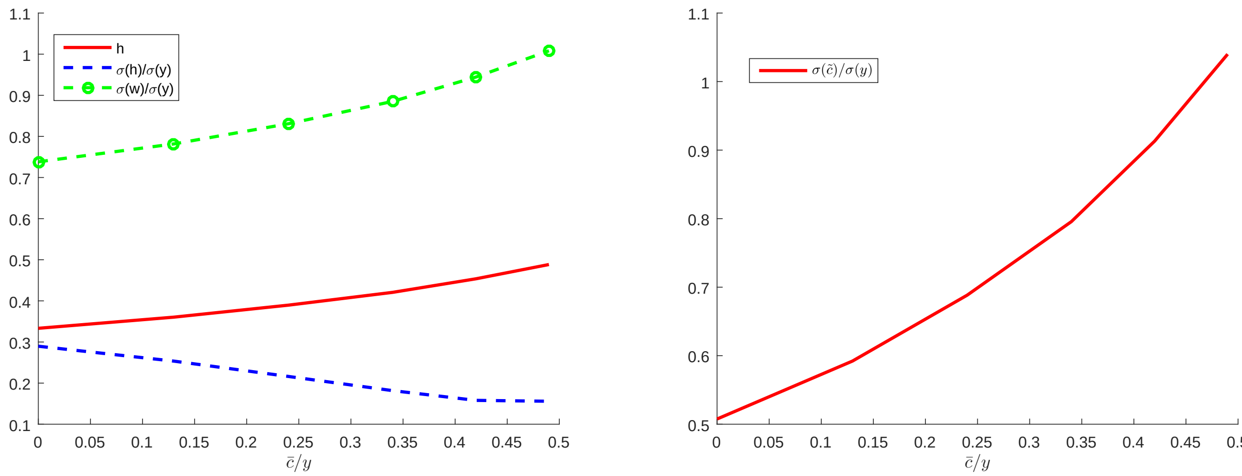


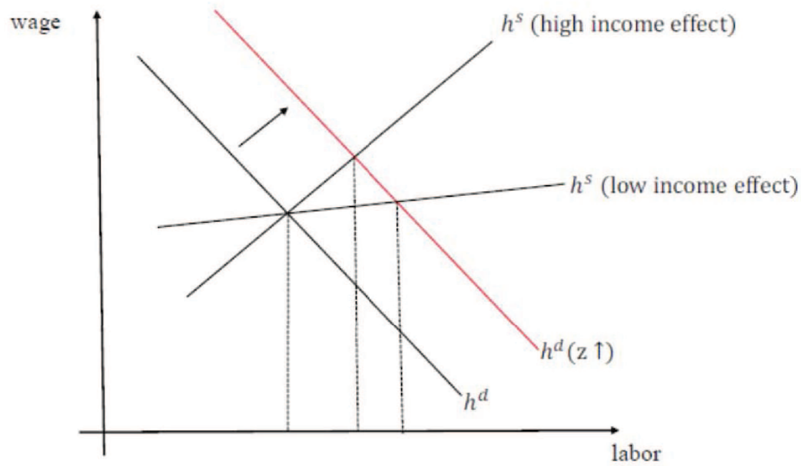
Figure 5.2a: Labor market behaviors

Figure 5.2b: Relative volatility of consumption

As noted by Bick, Fuchs-Schündeln, and Lagakos (2018), the introduction of subsistence consumption increases the income effect. Conceptually, this implies that the slope of the labor supply curve becomes steeper (hours worked responds less to a given change in real wages; see Figure 5.3). With a steeper labor supply curve, (i) hours worked 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 a similar logic. Lastly, a positive relationship between consumption volatility and subsistence consumption is straightforward. Given large changes in wages and small changes in hours worked, the labor supply equation that equates real wage and the 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.

In the previous section, we showed that contrary to the technology shock, responses of hours worked to the non-technology shock are not qualitatively different between developing and developed economies (Figure 3.5). For completeness of the analysis, we introduce a non-technology shock to the existing model

Figure 5.3: Description of the labor market



by altering the utility function as follows:

$$\upsilon_t \ln (c_t - \bar{c}) - \psi \frac{h_t^{1+\phi}}{1+\phi} \tag{5.7}$$

where υ_t follows an AR (1) shock similar to the technology shock (equation (5.6)).[27]

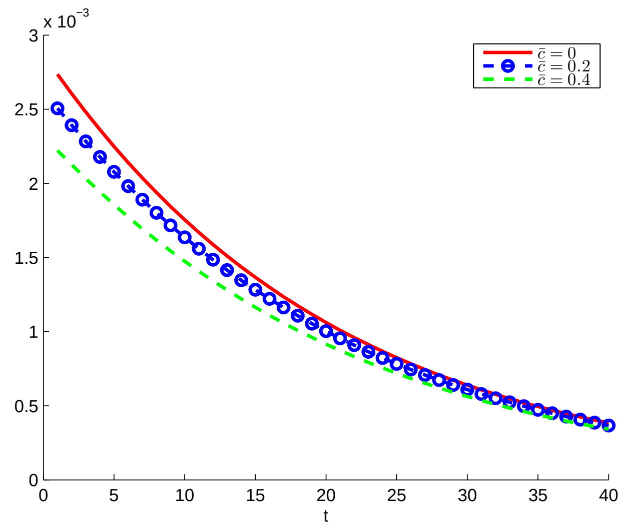
Impulse responses of hours worked to the one-time-one-unit negative shock to the demand (non-technology) shock are plotted in Figure 5.4. Consistent with the empirical evidence, the response of hours worked to the non-technology shock does not vary with the level of subsistence consumption. This is because the non-technology shock does not directly affect wages. Unlike the technology shock, the demand shock affects only the marginal rate of substitution without changing the marginal productivity of labor. Thus, gains from changing labor supply are limited, and the response of hours worked to the demand shock does not depend on the level of subsistence consumption.

One might argue that alternative structural factors might explain our empirical findings. For instance, in developing economies, price might be more rigid and (or) the financial market less developed. A model incorporating such features might explain our findings. To save space, we discuss the plausibility of alternative approaches in understanding our findings in the appendix B.

Lastly, while the common use of GHH preferences in many small open economy models in explaining

[27]Results are robust to alternative ways to incorporate demand shocks.

Figure 5.4: Response of hours worked to the non-technology shock: model prediction



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 together.

5.3 Discussion of alternative preference specifications

Can the adoption of alternative preferences explain our findings? In a class of standard RBC models with KPR preferences (King, Plosser, and Rebelo (1988)), there exist both the income effect and the substitution effect of the increase in real wages driven by a positive productivity shock. However, since the seminal work by Mendoza (1991), 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 in which the hours worked fall in response to a rise in trend productivity due to the wealth effect. Recently, Jaimovich and Rebelo (2009) developed 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:

$$u(c_t, h_t) = \frac{(c_t - \psi h_t^{\theta} X_t)^{1-\sigma} - 1}{1-\sigma}, \tag{5.8}$$

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

$$u(c_t, h_t) = \frac{(c_t(1 - \psi h_t^{\theta}))^{1-\sigma} - 1}{1-\sigma}, \tag{5.9}$$

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

$$u(c_t, h_t) = \frac{(c_t - \psi X h_t^{\theta})^{1-\sigma} - 1}{1-\sigma}, \tag{5.10}$$

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

In JR preferences, increasing the parameter γ toward 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 reconcile with higher consumption volatility in developing economies. Li (2011) conducts this type of analysis by varying the parameter γ.[28] As she departs from GHH preferences and move toward KPR preferences (by increasing γ), the response of consumption to the 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 related to consumption and labor market dynamics (relative variability of consumption and labor to output) in developing economies. Moreover, varying parameter γ alone cannot explain the difference in the steady-state behavior of hours worked documented in Boppart and Krusell (2016) and Bick, Fuchs-Schündeln, and Lagakos (2018).

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

6 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 in advanced economies. Together with other business cycle properties of developing economies such as the relative variability of hours worked (real wages) to output being 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 a technology shock.

To resolve this problem, we claim that subsistence consumption, whose importance is greater in less-developed economies, is 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, into our model to match a wider set of business cycle properties.

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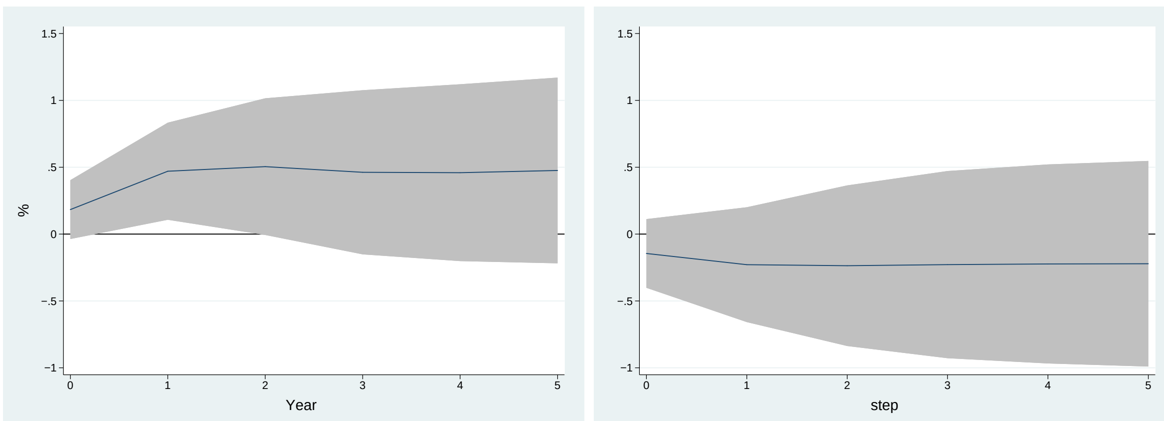
Appendix

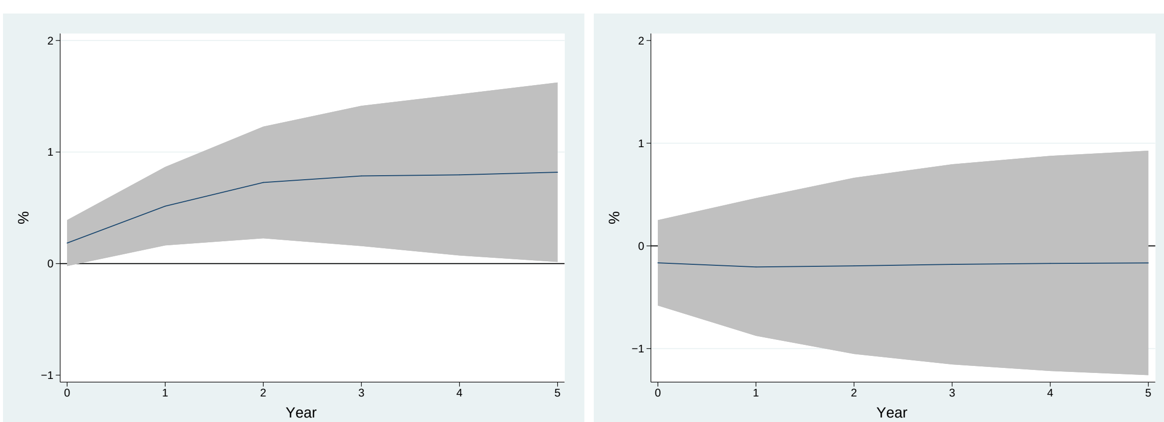
A Additional figures and tables

Figure A.1: IRF of hours worked to the group-specific permanent technology shock



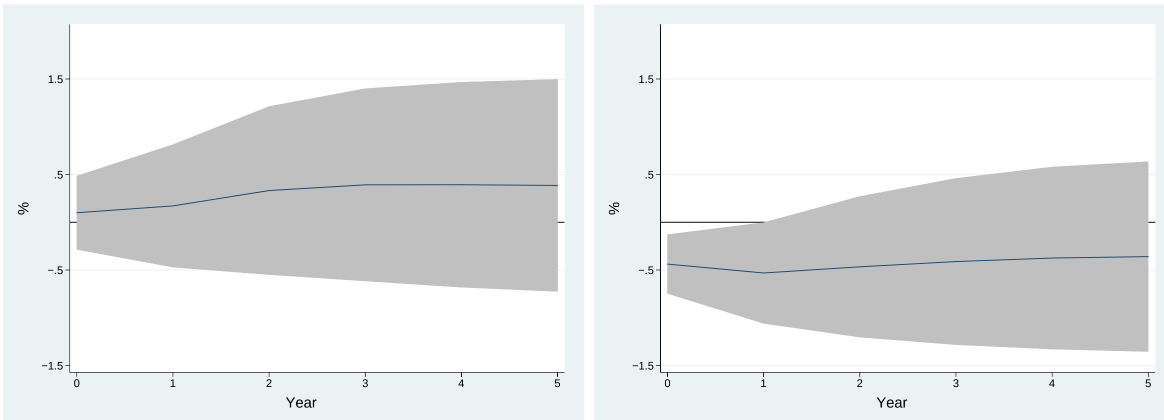
Note: This figure displays the impulse response function of hours worked to the permanent group-specific technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{Advanced,h}$, $\Delta h_t^{Advanced}$) in the left panel and developing economies ($\Delta z_t^{Developing,h}$, $\Delta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

Figure A.2: IRF of total employment to the group-specific permanent technology shock



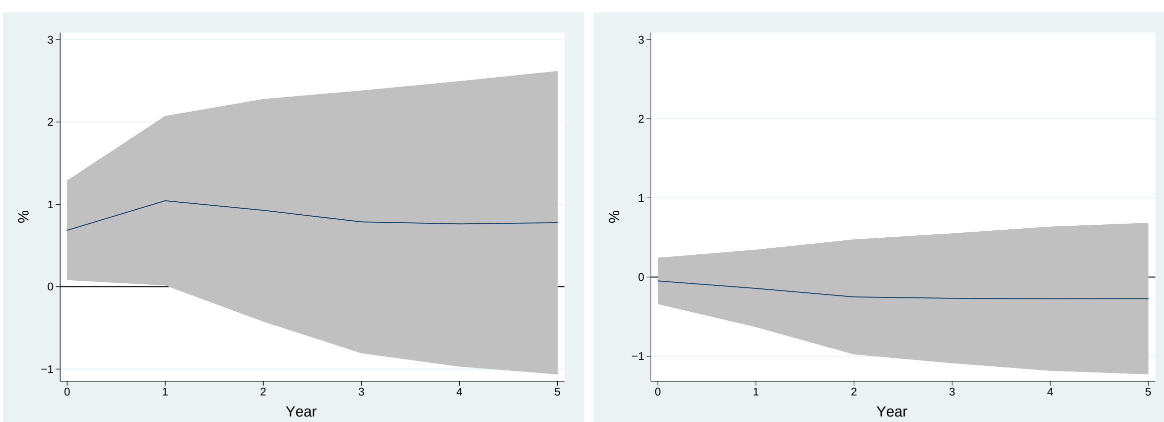
Note: This figure displays the impulse response function of total employment to the permanent group-specific technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{Advanced,n}$, $\Delta n_t^{Advanced}$) in the left panel and developing economies ($\Delta z_t^{Developing,n}$, $\Delta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

Figure A.3: IRF of hours worked to the permanent technology shock in developing economies: without LICs (left) and using advanced economy technology shock instead (right)



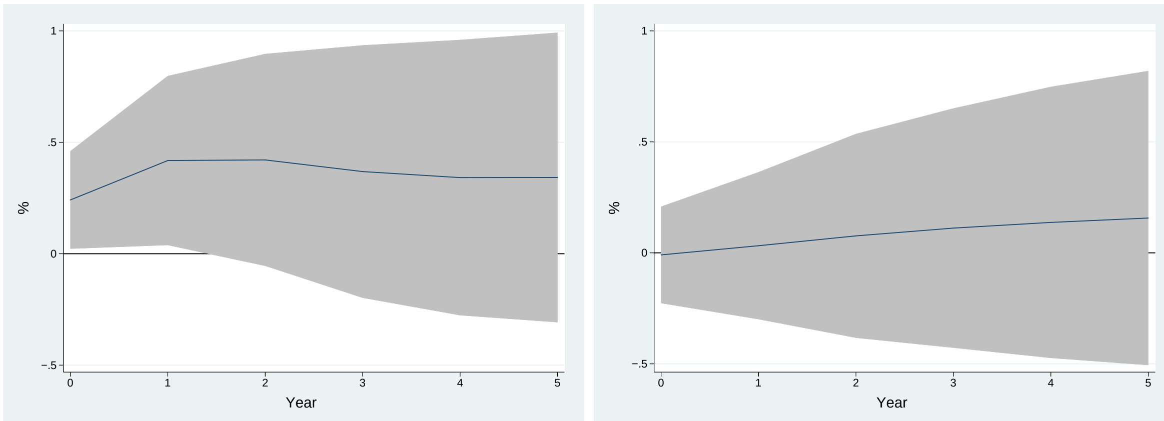
Note: This figure displays the impulse response function of hours worked to a permanent world technology shock in a bivariate VAR model of emerging economies without low-income countries $(\Delta z_t^{World,h}, \Delta h_t^{Emerging})$ in the left panel and the impulse response function of hours worked 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.4: IRF of hours worked to the world permanent technology shock since 1985



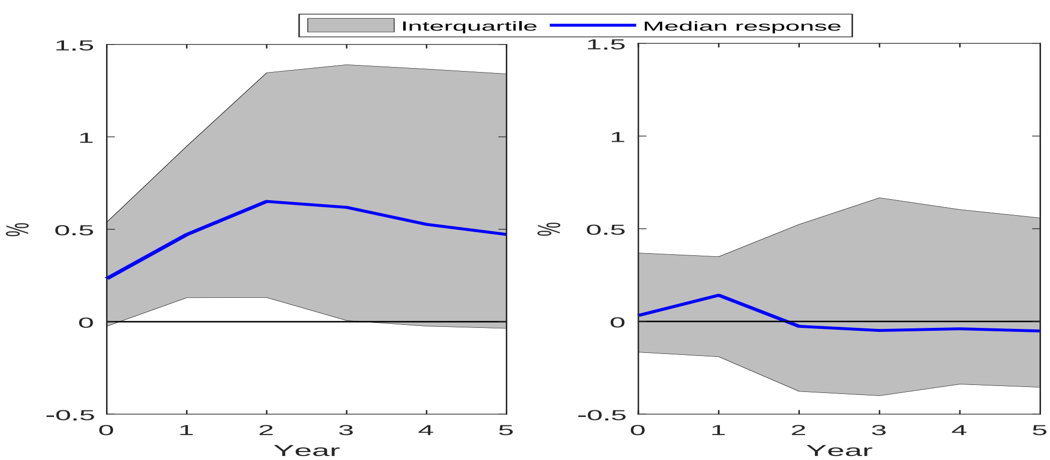
Note: This figure displays the impulse response function of hours worked to a permanent world technology shock in a bivariate VAR model of advanced economies $(\Delta z_t^{World,h}, \Delta h_t^{Advanced})$ in the left panel and developing economies $(\Delta z_t^{World,h}, \Delta h_t^{Developing})$ in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

Figure A.5: IRF of total employment to the world permanent technology shock using the full sample



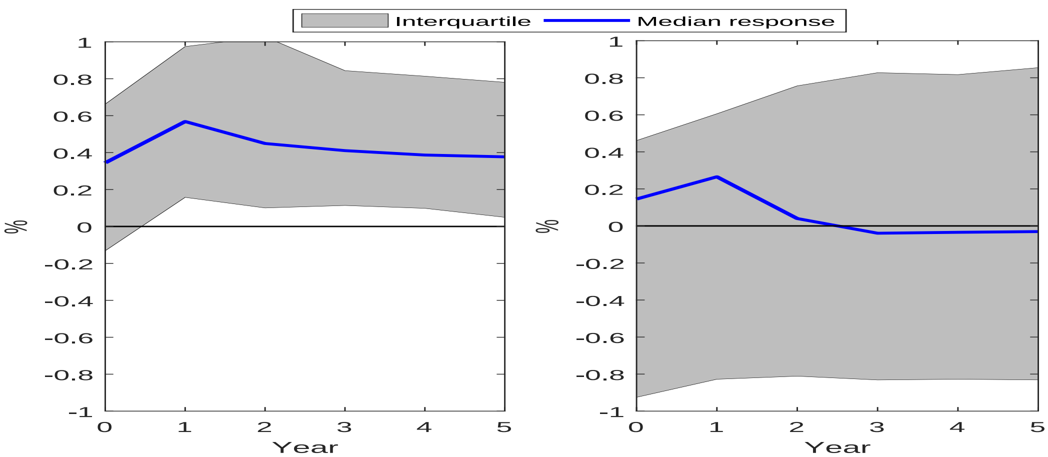
Note: This figure displays the impulse response function of total employment to a permanent world technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{World,n}, \Delta n_t^{Advanced}$) in the left panel and developing economies ($\Delta n_t^{World,n}, \Delta n_t^{Developing}$) 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.6: 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.

Figure A.7: 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: 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, as this approach is not necessarily the only way to explain the salient features of the data, we briefly review alternative models and test whether they can explain the set of empirical stylized facts. For brevity, we do not necessarily discuss every element of each model.

B.1 New Keynesian model with nominal price rigidities

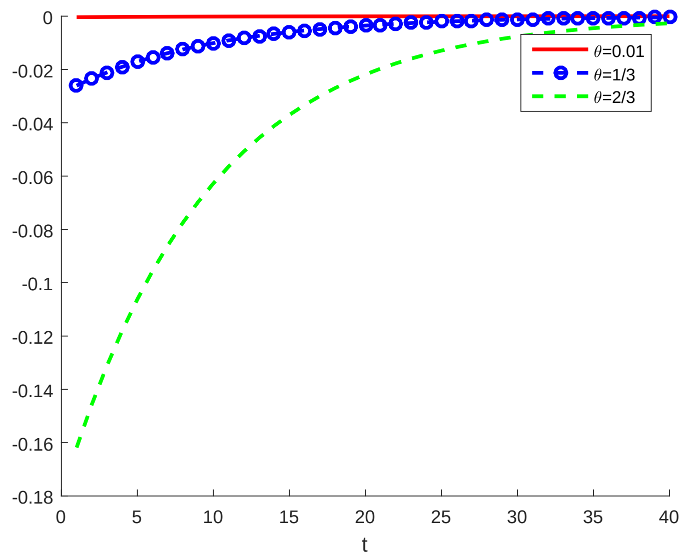
The first natural candidate to explain our empirical findings is the degree of price rigidities. As the negative response of hours worked to the permanent technology shock in Galí (1999) advocates an explanation based on a class of new Keynesian models with nominal price rigidities, one might argue that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

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. The details of the model are in Galí (2008). To observe see the implication of price rigidities, we vary the Calvo parameter, denoted as θ. Lower θ implies that prices become more flexible (the 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 this 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 the 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 parameter, but a function of a markup at the steady-state instead.[29]

[29] 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.

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



B.2 Model with trend growth shocks

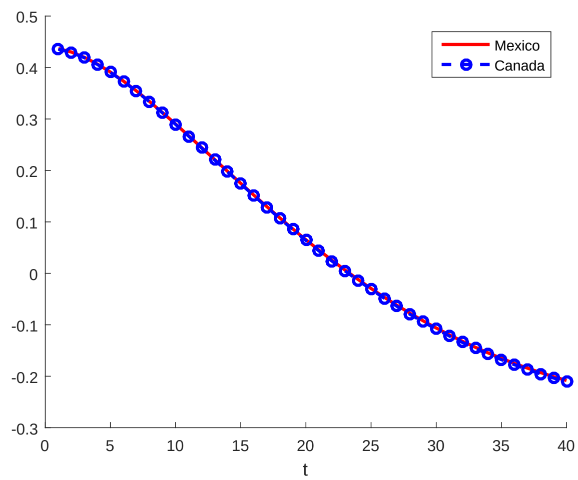
Another strand of the literature on emerging market business cycles has introduced an alternative shocks, such as a shock to trend growth (Aguiar and Gopinath (2007) among others) to explain their distinct business cycle properties. In this section, we discuss whether these models can explain our new empirical finding. We first test whether the model by Aguiar and Gopinath (2007) can generate a set of the stylized facts of 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 for 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 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.[30]

In their paper, two 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

[30]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.

report them in Figure B.2.[31] 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 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



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 choices 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)'s model.[32]

[31] 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).

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

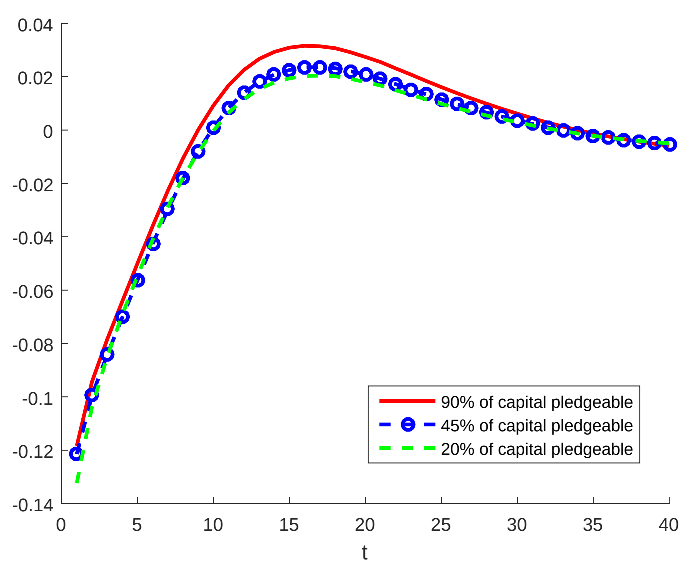
Again, we refrain from describing the full model. Instead, we discuss briefly how financial frictions are introduced into the model. First, impatient households face a borrowing constraint when buying houses. Second, entrepreneurs face similar a borrowing constraint. Let us consider the following simplified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

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

where l_t^e denotes the 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.[33] 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 is presented in Figure B.3.

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



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,

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

even when we impose unrealistically tight borrowing constraints.[34] The intuition is as follows. Suppose that financial frictions are so severe that workers (or firms) cannot access the financial markets at all. Labor income then becomes more important for these workers and higher wages 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.

[34] 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 does not substantially differ between the two groups.