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, which are distinct from those in advanced economies, then proposes a simple model 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 either short-run or long-run restrictions—is substantially smaller in developing economies. We then present compelling empirical evidence that several structural factors related to the relevance of subsistence consumption across countries can jointly account for the relative volatility of employment to output and that of consumption to output. We argue that a standard RBC model augmented with subsistence consumption can explain the several salient features of business cycle fluctuations in developing economies, especially 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; Vector Autoregressions

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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), studies on their labor market dynamics have 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 sharply different from those in developed economies. This paper aims to fill this gap in the literature by focusing on the labor market dynamics in developing economies.

The response of hours worked to technology shocks in advanced economies—especially the United States (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. Against this background, this paper examines the responses of hours worked and employment to the technology shock, using a structural Vector Autoregression (VAR) model with both short- (i.e., Cholesky) and long-run (à la Blanchard and Quah (1989) and Galí (1999)) restrictions. We exploit a large international panel dataset, including many developing economies over the last 45 years, and utilize both total factor productivity (TFP) and labor productivity for robust findings. To account for potential technology spillovers in the international setup and thereby seek robust findings, we estimate i) panel VARs with the country and time fixed effects and ii) VARs with aggregate measures of productivity and labor input. We find compelling 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 robust relationship between various structural factors proxying for the subsistence level of consumption, such as the share of agriculture, the size of the informal economy, and per-capita income, and the business cycle properties of consumption and labor variables. In particular, we show that the relative volatility (i.e., the second moment) of employment (consumption) is negatively (positively) correlated with the empirical proxies for the importance of subsistence consumption

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

across a large group of countries. However, other important structural factors distinguishing developing economies from advanced economies, such as trade openness, labor market regulations, and financial development, fail to explain the cross-country heterogeneity in the business cycle properties jointly.

Motivated by the above-stylized facts, we extend a canonical real business cycle (RBC) model by embedding subsistence consumption to the utility function. We find that the equilibrium properties of our model calibrated with a reasonable degree of subsistence consumption are fully consistent with the observed dynamics in developing economies. As the subsistence level of consumption increases (i.e., subsistence needs become more pressing), 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 (Bick, Fuchs-Schündeln, and Lagakos (2018); Boppart and Krusell (2020)) 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 respond less in an economy with a higher subsistence level of 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 become 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 main contribution to the literature is threefold. 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 these economies. Second, to the best of our knowledge, this paper is the first attempt to explain the economic fluctuations in developing economies using 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); Bick, Fuchs-Schündeln, and Lagakos (2018)), none of the previous studies have analyzed the business cycle properties in developing economies.[2] Third, our findings 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 (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. As a result, labor supply is fully responsive to current shocks, while wages do not adjust much, which contradicts the set of our empirical findings.[3]

The rest of this paper is organized as follows. We 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 can explain our findings. Section 5 introduces the RBC model with subsistence consumption and demonstrates its empirical relevance. Section 6 concludes. In Appendix C, 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.

2 Data and stylized facts

In the main analysis, we use 45 years of annual balanced data on total factor productivity (TFP), labor productivity, and total hours worked for the sample period between 1970 and 2014. 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 because 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,

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

[3]With this type of preference, 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.

but only for 14 OECD countries.[4]

We acquire most data from the widely-used Conference Board Total Economy Database and the Penn World Table 9.0, which provide extensive historical data on GDP, TFP, 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 workweek, statutory holidays, paid vacation and sick days, and days lost due to strikes, and are consistent with NIPA measures of output.[5] Labor productivity is defined as (i) output per hours worked (ratio of real output to total hours worked) or (ii) output per employed person (ratio of real output to persons employed).

Because our measure of labor productivity used in the alternative identification scheme requires the aggregation of output and labor across countries, our sample should be fully balanced. 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). The output is converted to the 2016 price level with updated 2011 PPPs, which allows for consistent aggregation across countries. For consistency, we use the balanced panel for the baseline model as well.

Stylized facts about the unconditional moments. Table A.1 in Appendix 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.[6] Compared to advanced economies, developing

[4]In the 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 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).

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

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

economies are characterized by smaller relative variability of both hours worked and employment to output, which corroborates the stylized fact in Neumeyer and Perri (2005) and Boz, Durdu, and Li (2015) by employing a substantially larger sample.[7] Table A.2 in Appendix A presents the full list of countries used in the robustness check using employment data.

3 Empirical findings from a structural VAR model

3.1 Measurement and identification 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. We do not identify an exact source of non-technology shocks, such as shocks to a preference, government spending, and monetary policy.

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. For example, Kose, Otrok, and Whiteman (2003), and Stock and Watson (2005) find a large contribution of common world shocks to macroeconomic variables in individual countries by estimating a factor model. 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 common world 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 common world shocks is not limited to developed economies. Dupaigne and Fève (2009) also suggest that the labor productivity of G7 countries cointegrates and displays a single stochastic trend, which calls for caution when using a country-by-country approach.

While it is possible to define a country-specific technology or productivity shock and estimate the VAR model country by country, this naive approach could bias the measurement of a technology shock to the extent that technology shocks spill over from one country to others. Moreover, given the limited

[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.

time-series availability for many developing countries, such a country-by-country analysis is likely to suffer from large standard errors, which prevents any meaningful conclusion. To resolve these issues, we adopt two different but complementing approaches in estimating the response of labor input to a technology shock in the international context. Since both approaches yield qualitatively similar estimation results, we report the results from the first approach (i.e., panel VAR model) in the main text and present the results from the second approach (i.e., aggregate VAR model) in Appendix B to save space.

Panel VAR model. First, we estimate the structural VAR model using the least square estimator with country-specific and time-specific dummies. We pool the data from a group of advanced and developing countries, respectively, then compare the response of labor input to the technology shock across the two groups. The panel for each group is fully balanced (1970-2014) to rule out the possibility that the different responses between the two groups are driven by different sample periods used for estimation.

We also introduce country-specific dummies, which correspond to the country fixed effect. This least square dummy variable estimator (LSDV) or fixed effect estimator is widely used to estimate panel VARs from macroeconomic data with a large time-series dimension (Uribe and Yue (2006); Akıncı (2013); Kim (2015)). While a potential concern with the panel VAR is the inconsistency of the LSDV estimates due to the combination of fixed effects and lagged dependent variables (Nickell (1981)), the inconsistency problem is unlikely a major concern because the time-series dimension of the data is quite large (45 years).[8]

We further allow for time dummies that are common across all countries in each group, which control for cross-country spillovers (i.e., international linkages). This empirical strategy is motivated by the recent empirical evidence that macroeconomic fundamentals across the world are typically driven by a common global dynamic factor (Kose, Otrok, and Whiteman (2003); Stock and Watson (2005)). See Canova and Ciccarelli (2013) and Abrigo and Love (2016) for further details of the estimation of panel VAR models.

The baseline VAR model includes two variables: TFP (TFP at constant national prices) and labor input series (total hours worked and employment), which are specific to each country. For this exercise, we use TFP as a measure of technology shocks because TFP is a more natural measure of technology when labor productivity reflects changes in the input mix as well as improved efficiency (Basu, Fer-

[8]As demonstrated by Kiviet (1995) and Judson and Owen (1999), an LSDV dynamic panel regression using lagged dependent variables performs relatively well when the time dimension is relatively large ($T \geq 30$).

nald, and Kimball (2006); Chang and Hong (2006)). It would be ideal to use the so-called "purified" technology series as in Basu, Fernald, and Kimball (2006) by controlling for nontechnological effects in aggregate total factor productivity (TFP): varying utilization of capital and labor, nonconstant returns and imperfect competition, and aggregation effects. However, these series are not available for most countries in our sample. We estimate the following bivariate panel VAR model for a group of advanced and developing economies separately:

$$Y_{i,t} = \sum_{j=1}^{p} B_j Y_{i,t-j} + \alpha_i + \tau_t + u_{i,t}, \tag{3.1}$$

where $Y_{i,t} = (\Delta z_{i,t}^{TFP}, \Delta h_{i,t})'$ and $u_{i,t} = (u_{1i,t}, u_{2i,t})'$ with $E[u_{i,t}u_{i,t}^{'}] = \Sigma$. α_i denotes country fixed effects and τ_t denotes time fixed effects. Because country fixed effects could be correlated with the regressors, we use a forward mean-differencing procedure with up to four lagged regressors as instruments for our GMM estimation. 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 $C(L) = (I_2 - B_1 L - ... - B_p L_p)^{-1}$ 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 technology shock is identified by a standard short-run restriction assuming that the technology shock measured by TFP has a contemporaneous effect on labor input, but the shock to labor input affects TFP only with a lag.

In this VAR model, it is crucial to choose an appropriate specification (levels vs. first-differences) of labor input (Christiano, Eichenbaum, and Vigfusson (2004); Francis and Ramey (2005); Pesavento and Rossi (2005)). Thus, we perform the panel unit root test by Im, Pesaran, and Shin (2003) and Table A.3 in Appendix provides the corresponding statistics for each measure of labor input for each group of countries. While the null hypothesis that all cross-sections contain unit-roots cannot be rejected for the (log) level specification, it is strongly rejected for the (log) first-difference specification, supporting the first-differences specification.[9] Figure A.1 in Appendix shows the average TFP growth for each group

[9]We also conduct the ADF test for labor input in each country. In most countries, we find that the null hypothesis of

of countries from 1970 to 2014.

Aggregate VAR model. Second, we estimate the structural VAR model using an aggregate measure of labor input and technology shocks that account for potential spillovers in technology shocks. Motivated by 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.[10]

The aggregation across countries offsets the country-level stationary shocks that contaminate country-level data, thereby mitigating the identification problem. Using this alternative identification scheme, Dupaigne and Fève (2009) find a positive impact response of employment to the permanent technology shock, which disputes Galí (1999)'s findings. 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 in our context.

However, one should note that such aggregation is not applicable to the case of TFP, which is obtained as structural residuals. Instead, we employ Blanchard and Quah (1989)'s long-run restrictions to identify permanent technology shocks using labor productivity as in Galí (1999). Compared to the panel VAR model, this alternative model is likely to suffer from large standard errors because we only use one time-series for the estimation of each group. Given the pros and cons of each identification scheme, we consider this alternative model as a complement to the panel VAR model. To save space, we do not report the results from estimating the aggregate VAR model in the main text. All of the estimation results of this exercise are summarized in Appendix B, which are qualitatively similar to those of the panel VAR model.

Following Dupaigne and Fève (2009), we consider a VAR model whereby labor productivity is defined as the ratio of real output aggregated over the 43 countries in the sample to total hours worked, which is also aggregated over the same sample. We use the PPP-adjusted GDP to take into account differences

the unit root cannot be rejected for the level of hours worked and employment, also lending support to the first-differences specification.

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

in purchasing power across countries, which better approximates the standard of living in each country. This so-called aggregate VAR model uses 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. We estimate the following bivariate VAR model for advanced and developing economies separately:

$$Y_t = \sum_{j=1}^{p} B_j Y_{t-j} + u_t, \tag{3.3}$$

where $Y_t = (\Delta z_t^h, \Delta h_t)'$ and $u_t = (u_{1,t}, u_{2,t})'$ with $E[u_t u_t^{'}] = \Sigma$. This alternative VAR model 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., $A_{12}(1) = 0$.

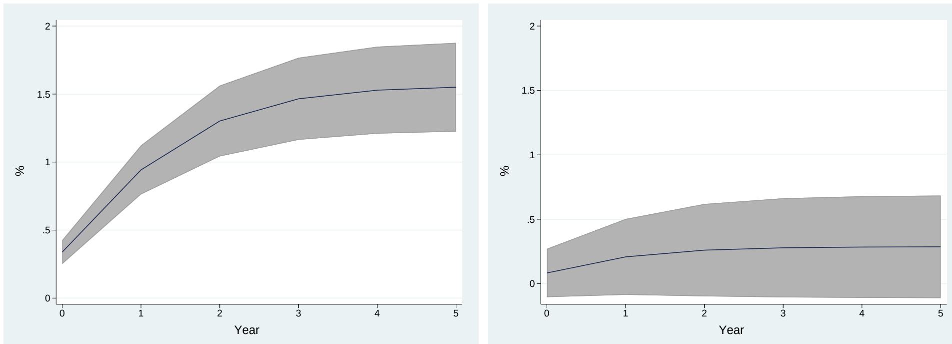
3.2 Main findings

We report the baseline results using the panel VAR model. Figure 3.1 displays the estimated responses of hours worked to the technology shock. The left panel reports the impulse response function (IRF) in the advanced economy group, and the right panel shows the IRF in the developing economy group. We obtain a 90% confidence interval by standard bootstrap techniques, using 500 draws from the sample residuals. On the one hand, hours worked increase significantly following the technology shock in the advanced economy group, which is consistent with the standard prediction of RBC models. The combination of the panel setup and the use of TFP instead of labor productivity generates a positive impact response of hours worked. On the other hand, hours worked do not respond much to the technology shock in the developing economy group. These findings shed light on the potential mechanism behind distinct business cycle moments of hours worked between advanced and developing economies presented in Table A.1.

We repeat our analysis using an alternative measure of labor input (employment). When we estimate equation (3.1), $Y_{i,t}$ becomes $(\Delta z_{i,t}^{TFP}, \Delta n_{i,t})'$, where $\Delta n_{i,t}$ is the growth rate of employment. We use the same set of countries where both hours worked and employment are consistently available from 1970. Figure 3.2 confirms that the significant response of labor input to the positive technology shock is only present in a group of advanced economies.[11]

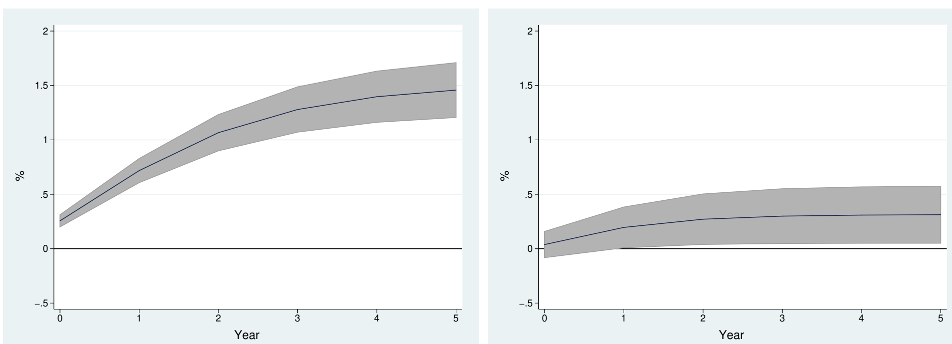
[11] Dropping the post-Global Financial Crisis period (from 2008) hardly affects the difference in the response of hours worked and employment to the world technology shock between the two groups.

Figure 3.1: IRF of hours worked to the technology shock



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

Figure 3.2: IRF of total employment to the technology shock



Note: This figure displays the impulse response function of total employment to the technology shock in a bivariate panel VAR model of advanced economies ($\Delta z_{i,t}^{TFP,Advanced}, \Delta n_{i,t}^{Advanced}$) in the left panel and developing economies ($\Delta z_{i,t}^{TFP,Developing}, \Delta n_{i,t}^{Developing}$) in the right panel and its 90% confidence interval from 500 bootstraps.

3.3 Robustness checks

We also conduct a battery of robustness checks. First, 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. Our analysis using group-specific time fixed effects may not capture the pattern of technology spillover during the pre-financial globalization era, resulting in biased estimates for the group of developing economies, in particular. Thus, we repeat our analysis using only the sample from 1985. Figure A.3 in Appendix shows that the responses of hours worked still differ between the two groups.[12]

Second, we have used only 43 countries in the analyses above because only these countries have sufficient time-series data on both TFP and hours worked. 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.4 in Appendix, both the qualitative and quantitative differences between advanced and developing economies in the response of employment to the technology shock, resemble the baseline results.

Lastly, 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 (see Figure A.5 in Appendix).

3.4 Additional VAR exercises

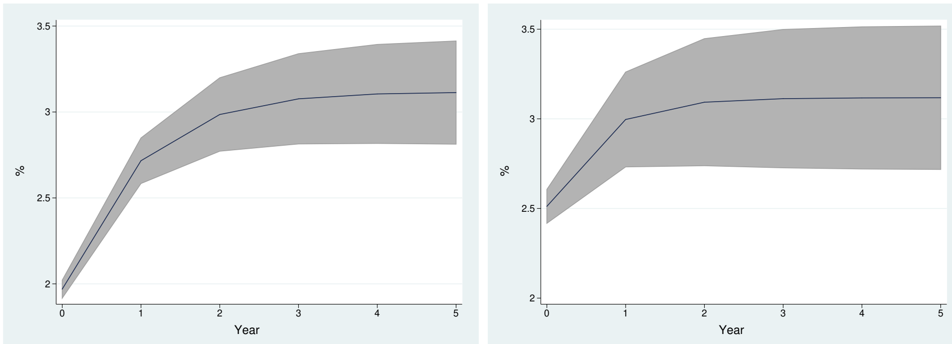
Thus far, we have only focused on the response of hours worked (or employment) to the technology shock. However, presenting additional IRFs could help understand the source of different properties of labor market dynamics and confirm the validity of our identification of structural shocks.

Response of hours worked to the non-technology shock. First, we estimate the response of labor input to the non-technology shock to test whether the response of labor input to the non-technology shock differs between advanced and developing economies. Figure 3.3 plots the response of hours worked to the non-technology shock, which is quite 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 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 the forecast error variance decomposition. Table 3.1 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 explains a non-negligible share of fluctuations in hours worked and

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

Figure 3.3: IRF of hours worked to the non-technology shock



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

employment for advanced economies, while the same shock explains virtually none of the labor market dynamics in developing economies. Together with evidence from Figure 3.3, Table 3.1 suggests that understanding the muted response of labor input to the technology shock in developing economies is key to understanding their distinct business cycle properties from advanced economies.

Table 3.1: Share of variation in labor input explained by the technology shock (%)

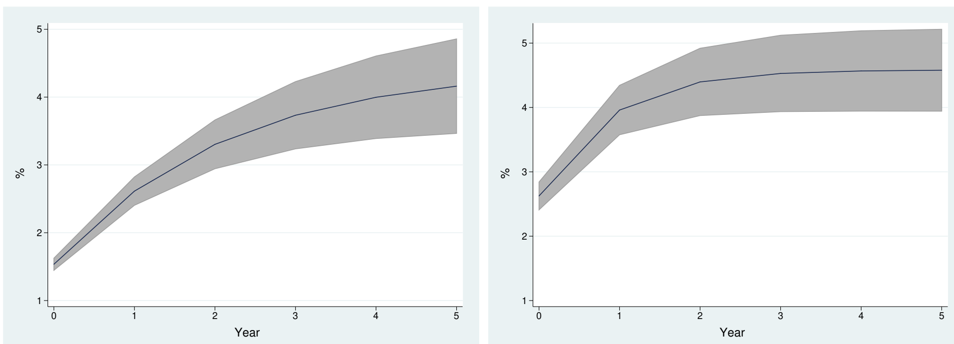
	Advanced economies		Developing economies	
Horizon	Hours worked	Employment	Hours worked	Employment
1	9.01	12.77	0.71	0.08
2	14.37	19.39	1.30	0.14
3	15.86	22.47	1.38	0.14
4	16.28	23.58	1.39	0.14
5	16.37	23.93	1.39	0.14

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

Response of real consumption to the technology shock. We have worked with a parsimonious bivariate VAR model, including only TFP and labor input variables, to study potential heterogeneity in the response of hours worked and employment to the technology shock, given our primary focus on 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 as a third variable in the VAR system. In other words, we replace $Y_{i,t} = (\Delta z_{i,t}^{TFP}, \Delta h_{i,t})'$ in equation (3.1) with $Y_{i,t} = (\Delta z_{i,t}^{TFP}, \Delta h_{i,t}, \Delta c_{i,t})'$, where $\Delta c_{i,t}$ is the annual growth in real consumption in country i.[13] Figure 3.4 shows that the positive effect on consumption is similar between two groups at the peak. If anything, the impact effect is larger in developing economies, which is in sharp contrast to the effects on hours worked and employment.

Figure 3.4: IRF of consumption to the technology shock



Note: This figure displays the impulse response function of consumption to the 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.

4 Economic development, subsistence consumption, and business cycle moments

How do we explain the set of stylized facts documented in the previous section? The following structural characteristics have been put forth in the literature as potential determinants of macroeconomic volatility, thereby providing a plausible explanation for our new empirical findings: (i) trade openness, (ii) financial development, (iii) government size, (iv) institutional quality, (v) labor market regulations, (vi) informal economy, (vii) the share of agriculture, and (viii) economic development.

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

[13] As long as we are interested in the response of hours worked and consumption to the technology shock, we are not particularly concerned about the restriction imposed on the structural relationship between hours worked and consumption. Our results still hold when we reverse the order between hours worked and consumption in the VAR model above.

governs the degree of technological spillovers and the quantitative role of terms of trade shocks across countries (Kose, Otrok, and Whiteman (2003)). We measure trade openness by the ratio of exports plus imports to GDP, as is standard in the literature. When available, we use the average of each factor over the sample period between 1970 and 2014 in the following exercises. Second, less developed financial markets 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)). 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)). Financial development is measured by the domestic credit provided by the banking sector as a percentage of GDP, which is also standard in the literature.

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. Government size measured by shares of government consumption in GDP. 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. 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).[14]

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. To capture institutional differences in labor market regulations across countries, we use the labor market regulation index taken from the Fraser Institute's Economic Freedom of the 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). Sixth, we consider the size of the informal economy as a potential candidate for explaining our empirical findings because its size is known to be correlated with the relative volatility of consumption to output (Restrepo-Echavarria (2014); Horvath (2018)). We use the widely used index

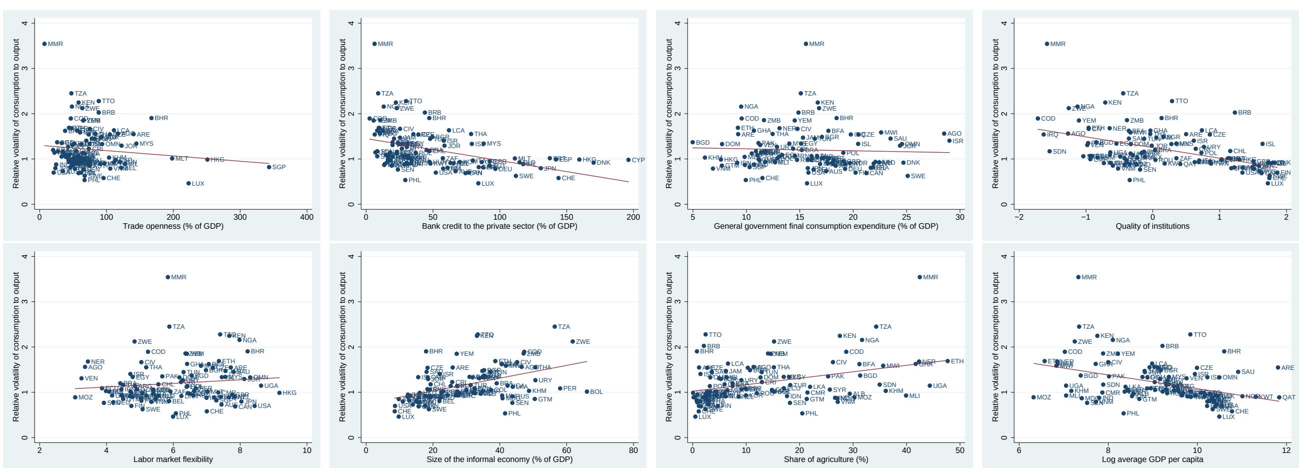
[14] The six subcategories are (i) control of corruption, (ii) government effectiveness, (iii) political stability and absence of violence/terrorism, (iv) regulatory quality, (v) rule of law, and (vi) voice and accountability.

by Schneider, Buehn, and Montenegro (2010) to measure the size of the informal economy.

Seventh, we attempt to explain our findings using the share of the agricultural sector in GDP motivated by the empirical pattern documented in Da-Rocha and Restuccia (2006) using the OECD data.[15] Regarding the importance of the agricultural sector in understanding business cycles, Yao and Zhu (forthcoming) show that the share of the agricultural sector is key to understanding the puzzling facts about aggregate employment fluctuations in China. Storesletten, Zhao, and Zilibotti (2019) also document that aggregate employment is uncorrelated with GDP in countries with large declining agricultural sectors. The share of agriculture is measured by Agriculture, forestry, and fishing value-added as a share of GDP. Lastly, we consider the level of per-capita income, which measures the degree of economic development as a last potential candidate.[16]

We first test whether the above candidate factors can explain one of the distinct business cycle properties of developing economies (higher relative consumption volatility than advanced economies) using a broad sample of countries. We plot the correlation between the relative volatility of consumption to output and the eight structural factors in Figure 4.1.

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



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

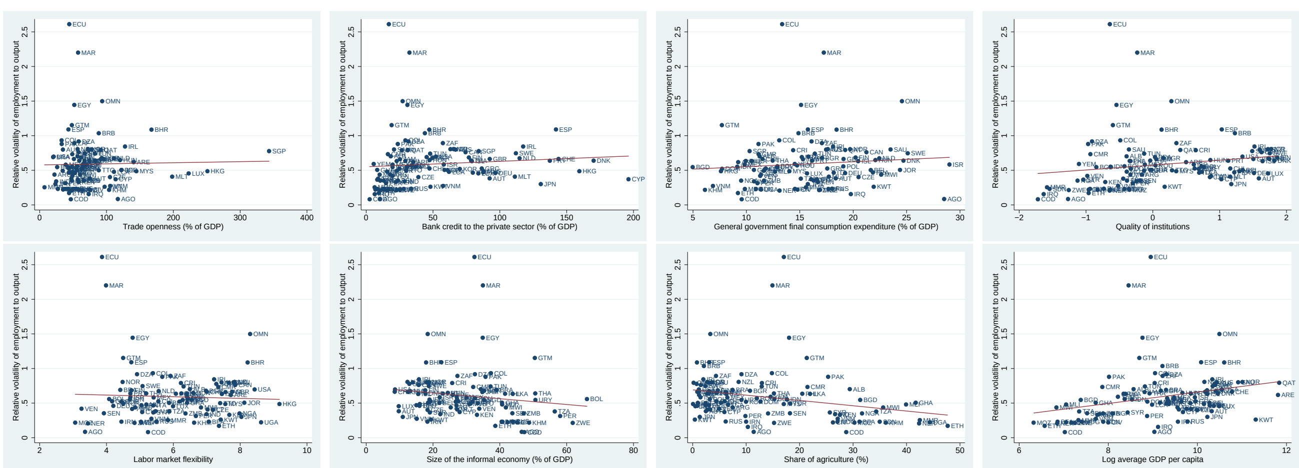
[15]Da-Rocha and Restuccia (2006) find that countries with a high share of employment in agriculture feature high fluctuations in aggregate output, the low relative volatility of aggregate employment, and low correlation of aggregate output and employment.

[16]In the previous version of the paper, we used PPP-adjusted per capita income as a proxy for the importance of subsistence consumption and obtained similar results. While the use of PPP-adjusted GDP is appropriate for comparison among developed countries, it is not appropriate when comparing developed countries with developing countries because substitution bias overestimates poor countries' income. We thank the anonymous referee for pointing this out.

Consistent with much of the literature, Figure 4.1 shows that the degree of financial development, institutional quality, the size of the informal economy, the share of agriculture, and per-capita income are strongly correlated with the relative volatility of consumption to output. The correlations are -0.42, -0.48, 0.46, 0.38, and -0.40, respectively, and all of them are statistically significant at 5%.

Given the lack of systematic attempts to explain the behavior of labor variables with the same set of structural factors, we contribute to the literature by asking whether these factors also explain the relative volatility of employment to output across countries. Figure 4.2 shows that the first five factors cannot explain the cross-country heterogeneity.[17] However, the last three factors can explain the heterogeneity in employment volatility (the correlation coefficients are -0.18, -0.26, and 0.28, which are statistically significant at 10%). In sum, these are the only structural factors that jointly explain the relative volatility of consumption and employment to output across a large group of countries.

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



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

Although subsistence consumption is a widely-used concept, its precise meaning is often not properly stated (Sharif (1986)), and it is difficult to obtain a country-specific empirical proxy that consistently available across many countries. Though not perfect, we believe that the last three factors, to a large extent, capture the importance of subsistence consumption across countries since subsistence consumption is likely to matter in a low-income country, which is often characterized by a higher reliance on agricul-

[17] All of the correlation coefficients are smaller than 0.15 in absolute values and none of them are statistically significant at 10%.

ture or the informal sector. Given the high correlation between the three variables, we do not further disentangle one from the others, and instead, highlight that these factors account for the stylized facts simultaneously.[18] In contrast, other structural factors, such as trade openness, financial development, institutional quality, and labor market flexibility, cannot explain the joint property of consumption and employment dynamics. Thus, the correlation analysis favors the subsistence consumption channel for understanding the distinct business cycle properties of developing economies.[19]

Table 4.1 shows that the subsistence consumption-income ratio—measured by the (universal) poverty line over country-specific per-capita income—is still not negligible in low- and lower-middle-income countries. Although subsistence consumption becomes largely irrelevant in advanced economies (high-income) or some emerging market economies (upper-middle-income), it is still an important characteristic of many developing economies.

Table 4.1: Poverty line over per-capita income

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

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

More evidence on the relevance of subsistence consumption. 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) noted, the relevance of subsistence consumption in determining the size of the income effect becomes smaller as the actual consumption level rises (i.e., the distance from the subsistence level increases). Boppart and Krusell (2020) 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. This further implies that subsistence consumption

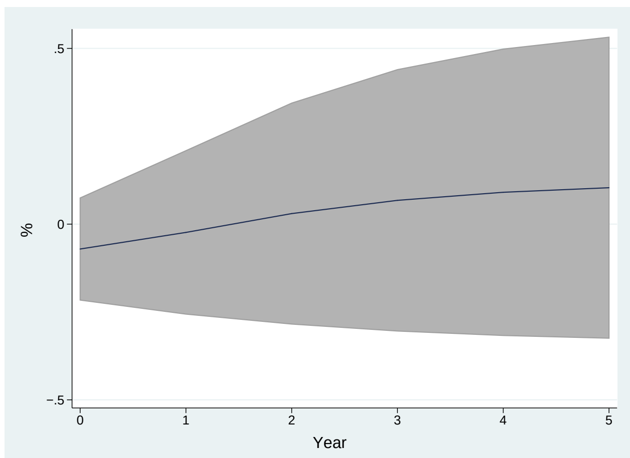
[18]The correlation between the average per-capita income (which is equivalent to the ratio of the poverty line to per-capita income) and the size of the agricultural economy is -0.54, and that between the average per capita income and the size of the informal sector is -0.48 in our sample and both are statistically significant at the 1 percent level.

[19]It would be interesting to distinguish the size of the informal sector and that of the agricultural sector from subsistence consumption and introduce all these three factors into a unified model framework to quantify the contributions of each channel. We leave this as future work.

can be a plausible candidate for explaining the set of our empirical findings.[20]

One might argue that the subsistence consumption channel is irrelevant for middle-income countries (i.e., emerging markets economies). As many middle-income emerging market economies were still 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 distinct labor responses to the technology shock between advanced and developing economies, we present the panel VAR results using the earlier data on a group of advanced economies from 1950 to 1970. As shown in Figure 4.3, the response of hours worked to the technology shock is muted in advanced economies when even these countries were not fully free of poverty and subsistence needs.

Figure 4.3: 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 technology shock in a bivariate panel VAR model of advanced economies ($\Delta z_{i,t}^{TFP,Advanced}$, $\Delta h_{i,t}^{Advanced}$) using the data from 1950 to 1970 and its 90% confidence interval from 500 bootstraps.

Moreover, we show that the relative volatility of hours worked to output in advanced economies stops increasing over time once their per-capita income far exceeds the level of subsistence consumption.[21] The left panel in Figure 4.4 compares the relative volatility of hours worked to output during 1950-1970, when subsistence consumption were relevant even for advanced economies, with that during 1971-1995.

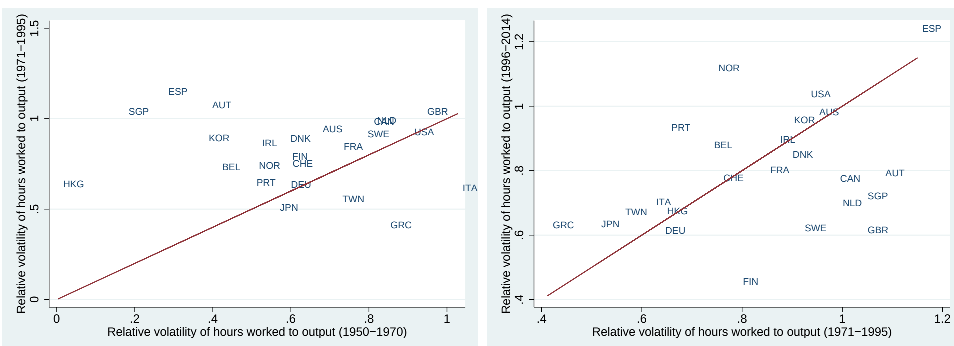
[20]In a related study, Ohanian, Raffo, and Rogerson (2008) find that the standard growth model appended to include taxes and a modest subsistence consumption effect performs better in capturing the large differences in trend changes in hours worked across countries, in terms of both the overall changes 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 across countries and over time.

[21]In this exercise, we use 24 advanced economies where hours worked data are available since 1950.

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, labor market regulations, and trade openness, advanced economies share an interesting pattern. As subsistence consumption loses relevance for this group of countries with earlier economic development, the relative volatility of hours worked to output tends to increase. However, the right panel in Figure 4.4 shows that additional economic growth since the 1970s is not associated with a further increase in the relative volatility of hours worked to output.[22] Though only suggestive, such a pattern found in the time-series data provides another support to the role of subsistence consumption in understanding the distinct labor market dynamics under technology shocks.[23]

Figure 4.4: 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).

5 RBC model augmented with subsistence consumption

We have established robust stylized facts about the response of hours worked and employment to the technology shock. Combined with the distinct business cycle properties of developing economy labor markets (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

[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 (2020) for the consistent finding of changes in the average hours worked in advanced economies and the income effect over time.

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 findings 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 (i.e., subsistence needs become more pressing), the response of hours worked to the technology shock becomes smaller. To the extent to which subsistence consumption is more relevant in less-developed economies (Table 4.1), this equilibrium property is consistent with our empirical findings.

To be more specific, the subsistence consumption channel is captured by equation (5.3). h^* increases with $\bar{c}$. Workers should work more to keep their consumption level above the subsistence level, which explains higher steady-state hours worked in poor countries. Thus, the disutility from working is higher in this economy. 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 to provide a set of quantitative predictions. We consider the following social planner's problem:

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

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 introduced to the utility function in a Stone-Geary form; log utility is considered to ensure the balanced growth path of our model. 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, we define $\tilde{c}_t \equiv c_t - \bar{c}$ and use it in the following analysis.[24]

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

Calibrated parameter values are reported in Table 5.1. We note that our results do not depend much on these 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

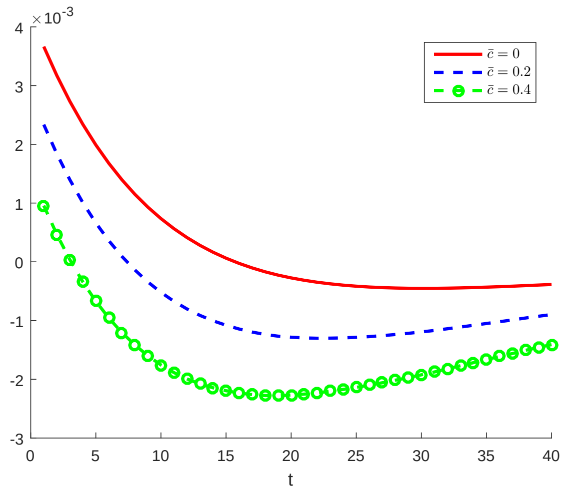
Predictions of the model. We first test if the behavior of our model is consistent with our empirical findings. Figure 5.1 plots the IRFs of hours worked to one-time-one-unit shock to technology. If subsistence consumption is zero—proxying an advanced economy like the United States—, the model economy 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 the subsistence level of consumption increases, the response of hours worked to the technology shock becomes smaller, 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 findings 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 the income-level and hours-wage elasticity.[26]

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

[25] One might argue that habit formation (Francis and Ramey (2005)), instead of the subsistence consumption, can explain our findings ($\ln(c_t - \alpha c_{t-1})$ with $\alpha > 0$ for example). Under this assumption with an external habit, it can be shown that higher hours worked in developing economies can be obtained with a 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.

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

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



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 to 0.5. The solid red line in Figure 5.2a shows that the steady-state hours worked is increasing in subsistence consumption. The intuition is already discussed in the previous section. The green dotted line and the blue dotted line describe how the relative volatility of hours worked to output and the relative volatility of real wages to output vary with $\bar{c}/y$, respectively. They replicate the empirical regularity found in Figure 4.1 and 4.2 successfully and also corroborate the findings of Aguiar and Gopinath (2007) and Boz, Durdu, and Li (2015).

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 respond 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

Figure 5.2: Dynamics of the model economy

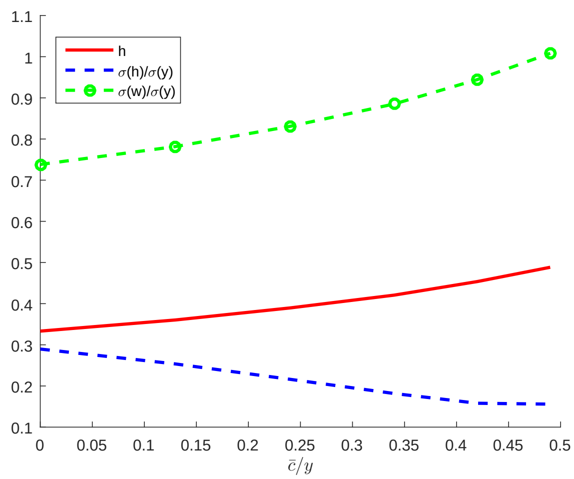


Figure 5.2a: Labor market behaviors

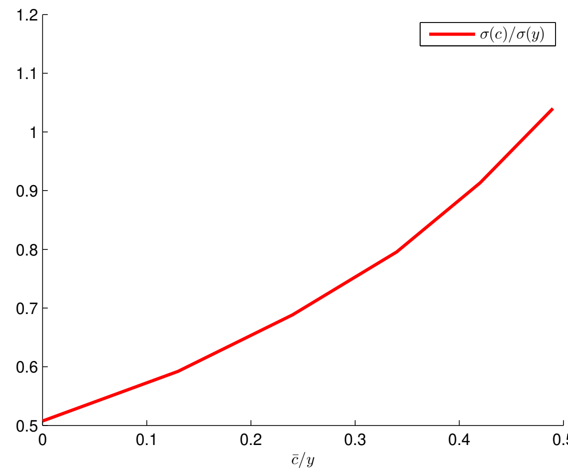
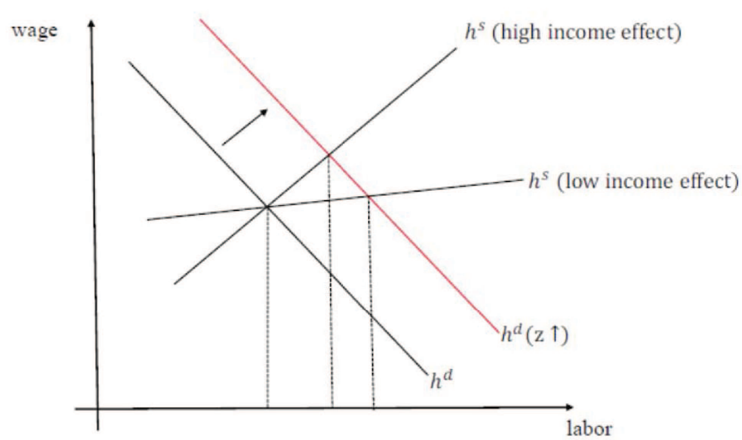


Figure 5.2b: Relative volatility of consumption

subsistence consumption level rises. 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 a further increase in consumption to match the greater wage response in the economy with higher subsistence consumption.

Figure 5.3: Description of the labor market



To examine the quantitative importance of the subsistence consumption channel, we consider the ratio between the relative volatility of hours worked to output in developing economies and that in developed economies, 0.84 (Table A.1). Take the weighted average of the poverty line in Table 4.1, which is about 0.17 (ratio I), as a reasonable value for subsistence consumption; Figure 5.2a implies that the above ratio is about 0.83 in the model economy, quantitatively consistent with the data.

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 3.3). For completeness of the analysis, we introduce a non-technology shock to the existing model 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.

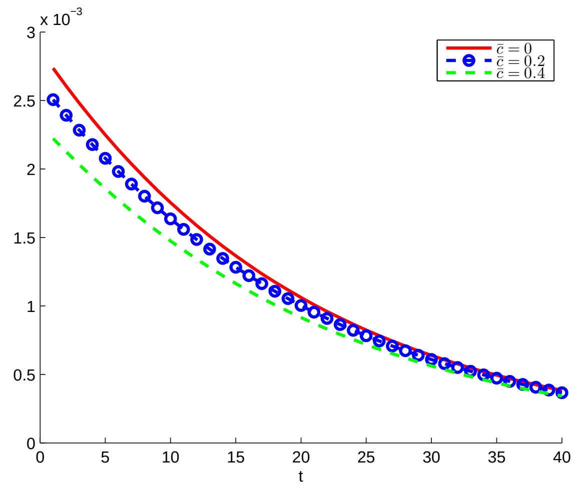
Appendix C provides a discussion on whether alternative modeling approaches, such as incorporating price rigidities, financial frictions, or trend shocks, explain the set of empirical findings. In sum, embedding these properties does not appear to improve the model's ability to explain distinct labor market dynamics in developing economies.

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

[27] AR (1) coefficient ($\rho = 0.95$) and standard deviation ($\sigma = 0.01$) of the demand shock are chosen to be the same with those of the TFP shock. Results are robust to alternative ways to incorporate demand shocks.

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



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. However, GHH preferences adopted to explain the distinct consumption dynamics in developing economies (Mendoza (1991), 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 developing economies suggests that the wealth effect is crucial in understanding the business cycle properties of these economies. We discuss briefly why the adoption of alternative preferences cannot improve the model to jointly explain consumption and labor market dynamics.

Recently, Jaimovich and Rebelo (2009) developed a utility function (JR preferences) that allows one to parameterize the strength of the short-run wealth effect on labor supply. This utility function 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. Moreover, varying the parameter γ alone cannot explain the difference in the steady-state behavior of hours worked.

6 Conclusion

Applying a structural VAR model with both short- and long-run restrictions to large international data of both advanced and developing economies, we document a novel empirical finding that the response of hours worked (and employment) to a 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 their 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 empirical findings of the labor market dynamics in these economies.

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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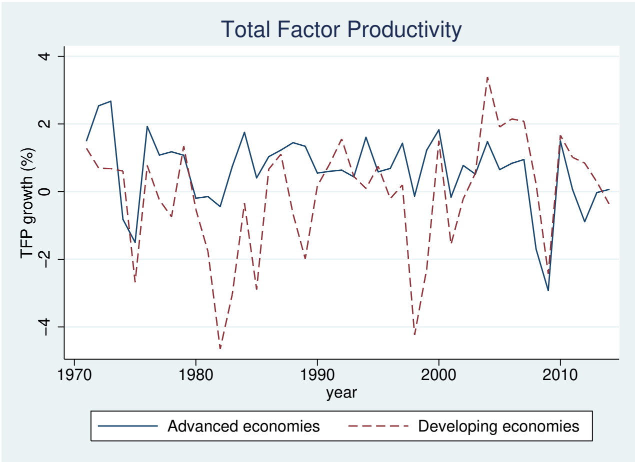
Online Appendix

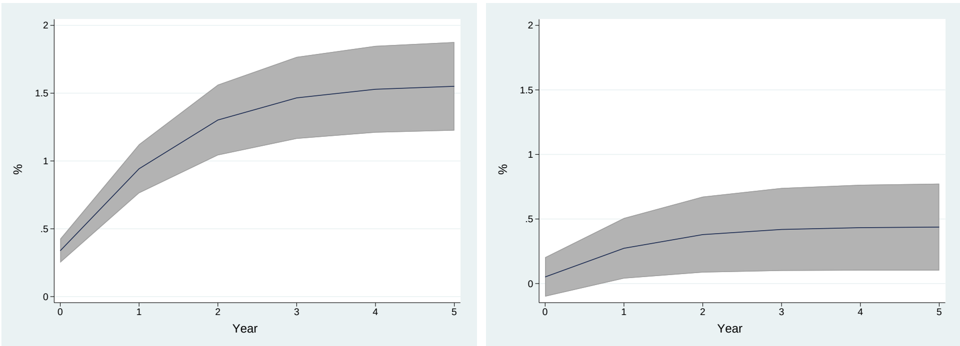
A Additional figures and tables

Figure A.1: The evolution of TFP growth over time



Note: This figure displays the average TFP growth for advanced and developing economies.

Figure A.2: IRF of hours worked to the technology shock without LICs



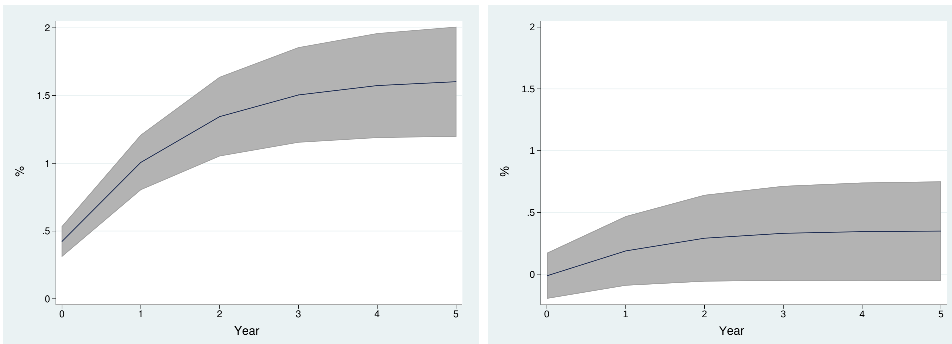
Note: This figure displays the impulse response function of hours worked to the technology shock in a bivariate VAR model of advanced economies ($\Delta z_{i,t}^{TFP,Advanced}$, $\Delta h_{i,t}^{Advanced}$) in the left panel and emerging economies without low-income countries ($\Delta z_{i,t}^{TFP,Emerging}$, $\Delta h_{i,t}^{Emerging}$) in the right panel and its 90% confidence interval from 500 bootstraps.

Table A.1: Countries used in the main 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

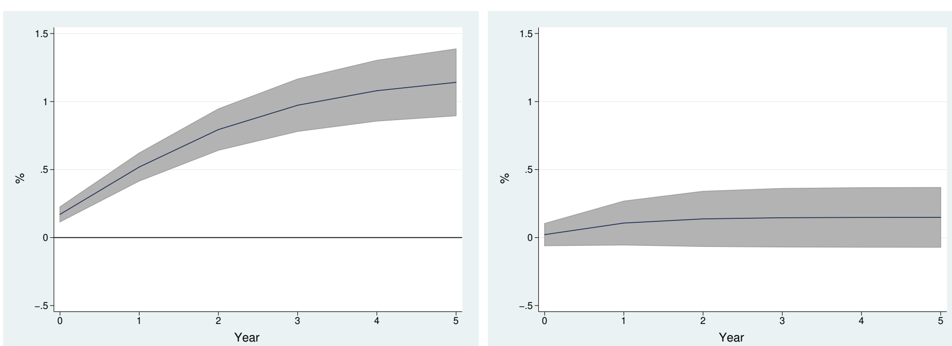
Note: σ denotes the standard deviation of the variable and ρ denotes the correlation between the variables. All series are HP-filtered using a smoothing parameter of 100. h, n, c, and y denote hours worked, employment, consumption, and output, respectively. * denotes a country belonging to the low-income 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.

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



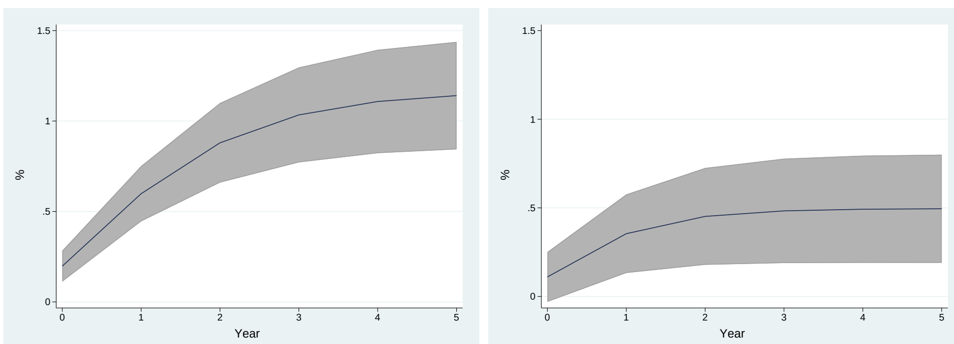
Note: This figure displays the impulse response function of hours worked to the technology shock in a bivariate VAR model of advanced economies ($\Delta z_{i,t}^{TFP,Advanced}, \Delta h_{i,t}^{Advanced}$) in the left panel and developing economies countries ($\Delta z_{i,t}^{TFP,Developing}, \Delta h_{i,t}^{Developing}$) in the right panel and its 90% confidence interval from 500 bootstraps.

Figure A.4: IRF of total employment to the technology shock using the large sample



Note: This figure displays the impulse response function of total employment to the technology shock in a bivariate panel VAR model of advanced economies ($\Delta z_{i,t}^{TFP,Advanced}, \Delta n_{i,t}^{Advanced}$) in the left panel and developing economies ($\Delta z_{i,t}^{TFP,Developing}, \Delta n_{i,t}^{Developing}$) in the right panel and its 90% confidence interval from 500 bootstraps.

Figure A.5: IRF of hours worked to the technology shock using the alternative sample



Note: This figure displays the impulse response function of total employment to the technology shock in a bivariate panel VAR model of advanced economies ($\Delta z_{i,t}^{TFP,Advanced}, \Delta n_{i,t}^{Advanced}$) in the left panel and developing economies ($\Delta z_{i,t}^{TFP,Developing}, \Delta n_{i,t}^{Developing}$) in the right panel and its 90% confidence interval from 500 bootstraps.

Table A.2: 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	Côte 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.

Table A.3: Panel unit root test on hours worked and employment

	Z-statistic (level)	p-value	Z-statistic (difference)	p-value
Hours worked				
World	2.814	0.997	-20.476	0.000
Advanced	2.384	0.991	-13.978	0.000
Developing	1.516	0.935	-15.414	0.000
Employment				
World	3.870	0.999	-18.275	0.000
Advanced	4.023	0.999	-11.113	0.000
Developing	1.118	0.868	-15.522	0.000

Note: The results from panel unit root test (Im, Pesaran, and Shin (2003)) are presented. H_0: All panels contain unit roots. H_a: Some panels are stationary.

B Additional estimation results using the alternative VAR model

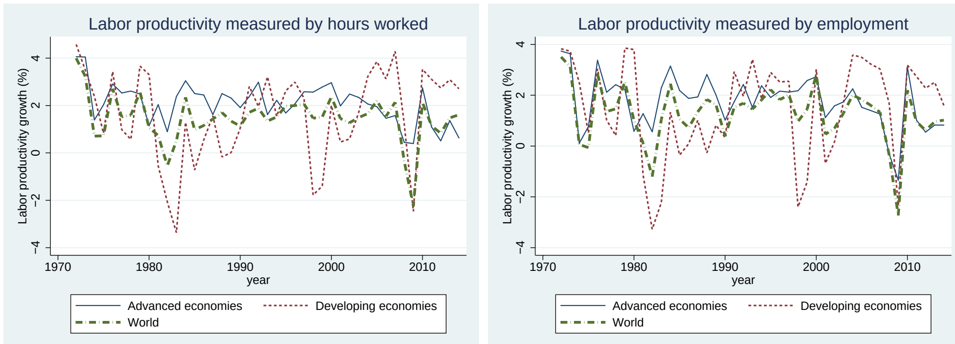
As indicated in the main text, this section provides all the estimation results from the alternative VAR model suggested by Dupaigne and Fève (2009) using an aggregate measure of world labor productivity. Dupaigne and Fève (2009) replicate Galí (1999)'s estimation of the short-run response of labor input 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 similar to Galí (2004). 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. In particular, 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. Thus, the estimation of this alternative model further mitigates concerns regarding a potential bias induced by technology spillovers. We provide a discussion of the results in parallel with the baseline panel VAR model in the main text.

First, Figure B.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. Group-specific labor productivity for each group in Figure B.1 shows a qualitatively similar pattern from the average TFP for each group shown in Figure A.1, although a decline in labor productivity during the global financial crisis is less pronounced than TFP for advanced economies.

Figure B.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. Table B.1 summarizes the results of the ADF test with two lags (including a time

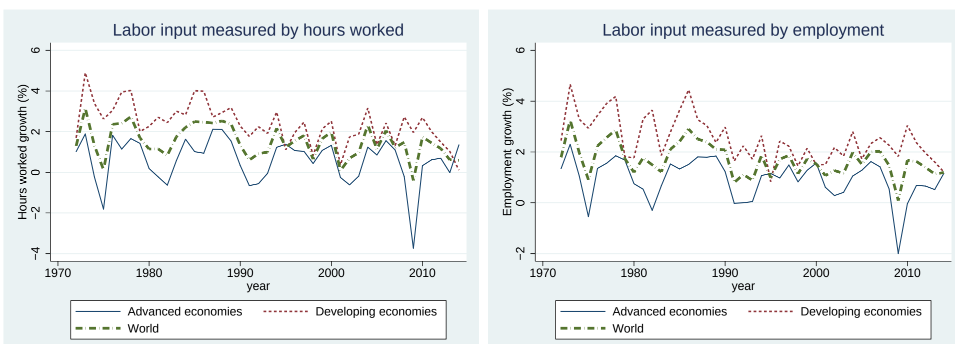
Figure B.1: The evolution of labor productivity over time: hours worked vs. employment



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.

trend), which supports the first-differences specification as in the panel unit root test.

Figure B.2: Aggregate labor input: hours worked vs. employment



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

Consistent with the panel VAR model, we also adopt a difference specification here. We perform the Augmented Dickey Fuller (ADF) test for unit root in labor input of each group. For each group, 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 B.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.

Table B.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.

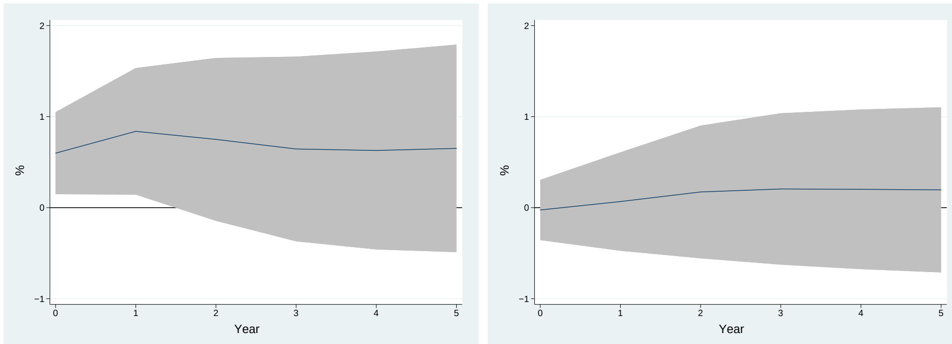
B.1 Baseline results

Figure B.3 displays the estimated responses of aggregated hours worked to the world permanent productivity shock. The left panel reports the 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. Similar to the baseline panel VAR model, we obtain a 90% confidence interval by standard bootstrap techniques, using 500 draws from the sample residuals.

The strong and statistically significant response of hours worked in the advanced economy group, and the weak and statistically insignificant response in the developing economy group are consistent with the baseline results of the panel VAR model. As argued by Dupaigne and Fève (2009), aggregating productivity over countries resolves the technology-hours worked puzzle raised by Galí (1999) for the advanced economy group. While the point estimates are essentially zero over the five-year horizon for the developing economy group, the confidence interval of estimates is narrower than the advanced economy group, suggesting that the result is not simply driven by larger standard errors for the developing economy group.

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 (3.3), Y_t becomes $(\Delta z_t^n, \Delta n_t)'$, where Δn_t is the growth rate of total employment. Again, Figure B.4 confirms that the significant response of labor input to the positive permanent tech-

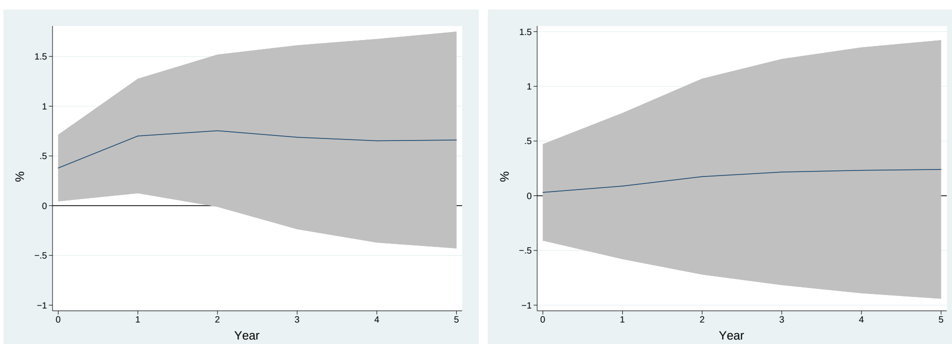
Figure B.3: IRF of hours worked to the world permanent technology shock



Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate aggregate 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.

nology shock—as predicted by a class of standard RBC models—is only present in a group of advanced economies).[28]

Figure B.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 aggregate 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.

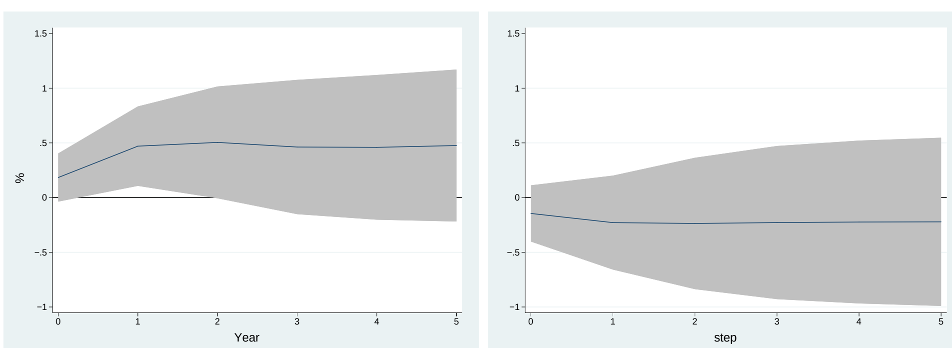
[28]Dropping the post-Global Financial Crisis period (from 2008) hardly affects the difference in the response of hours worked and employment to the world technology shock between the two groups.

B.2 Robustness checks

In this section, we provide the results from a battery of robustness checks. First, we have assumed that 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, Otrok, and Whiteman (2003) show that enhanced global spillovers of macroeconomic fluctuations due to trade and financial integration is mostly limited to advanced countries.

Thus, we 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 only, under the assumption that technology spillover occurs mainly among countries with a similar income level. Figure B.5 in Appendix displays the results using group-specific technology shocks, suggesting that the weaker response of hours worked to the permanent technology shock in developing economies is not merely because the technology level of these countries is far from the world technology frontier, such as the United States. This finding hardly changes when using employment instead (Figure B.6).

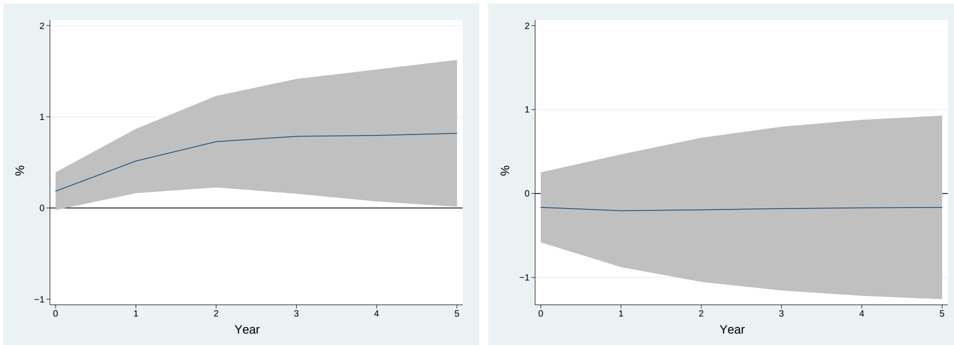
Figure B.5: IRF of hours worked to the group-specific permanent technology shock



Note: This figure displays the impulse response function of hours worked to the permanent group-specific technology shock in a bivariate aggregate 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.

Second, as in the baseline panel VAR model, we repeat our analysis after dropping a set of low-income countries. Because this modification affects only developing countries, we do not report the results for advanced economies. The left panel in Figure B.7 shows that our findings are not driven by

Figure B.6: IRF of total employment to the group-specific permanent technology shock



Note: This figure displays the impulse response function of total employment to the permanent group-specific technology shock in a bivariate aggregate 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.

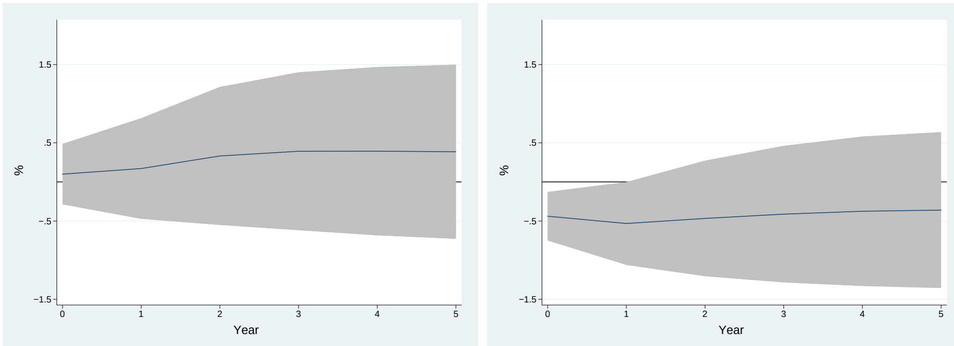
the inclusion of LICs.

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." Because this modification affects only developing countries, we do not report the results for advanced economies. The right panel in Figure B.7 confirms that the alternative measure of the technology process does not alter our conclusion.

Fourth, as in the baseline panel VAR model, we repeat our analysis using only the sample from 1985. 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. Figure B.8 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 Figure B.5, 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.

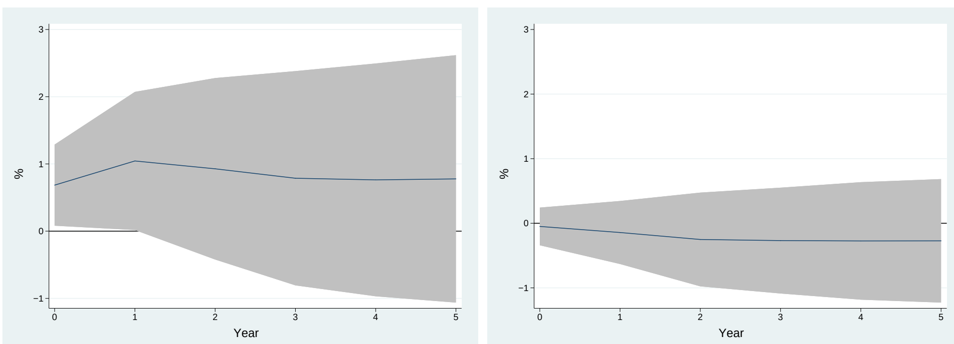
Fifth, as in the baseline panel VAR model, we repeat our analysis using a larger set of countries where employment data are available. Figure B.9 confirms that the results still hold when using a

Figure B.7: IRF of hours worked to the permanent technology shock in developing economies: without LICs (left) and using advanced economy technology shock instead (right)



Note: This figure displays the impulse response function of hours worked to a permanent world technology shock in a bivariate aggregate 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 aggregate 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 B.8: IRF of hours worked to the world permanent technology shock since 1985



Note: This figure displays the impulse response function of hours worked to a permanent world technology shock in a bivariate aggregate 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.

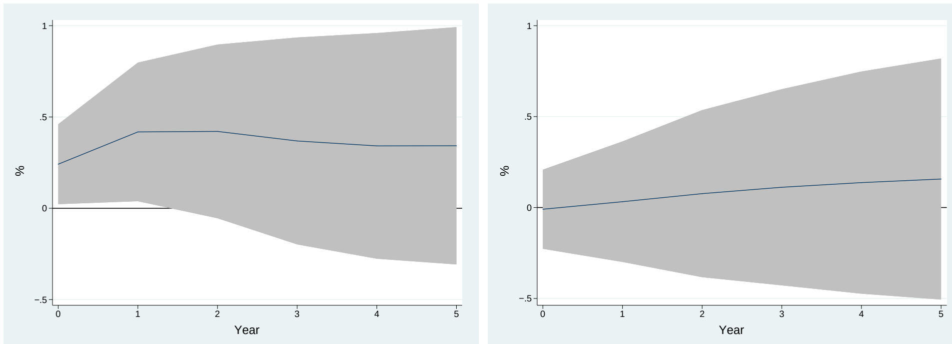
substantially larger sample of 103 countries.[29]

B.3 Additional VAR exercises

Response of hours worked to the non-technology shock. As in the panel VAR model, we estimate the response of labor input at the group level to the non-technology shock, which includes all

[29] 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.

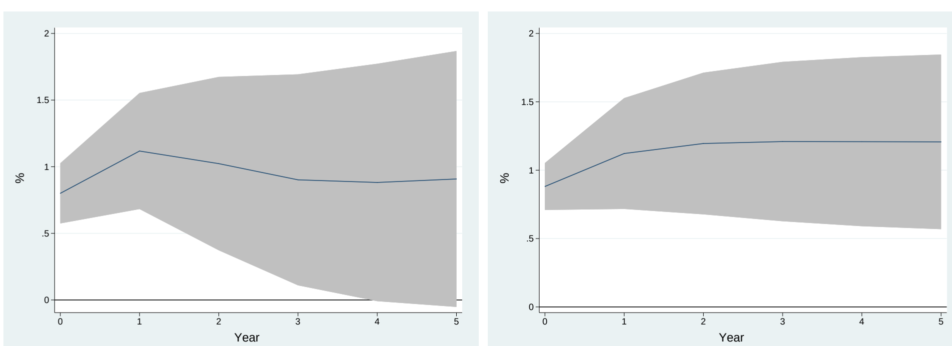
Figure B.9: IRF of total employment to the world permanent technology shock using the full sample



Note: This figure displays the impulse response function of total employment to a permanent world technology shock in a bivariate aggregate 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.

kinds of disturbances that do not have a long-run effect on world labor productivity. Figure B.10 plots the response of hours worked to the non-technology shock. Consistent with the panel VAR evidence, the responses of hours worked to the non-technology shock are remarkably similar between the two groups of countries using the alternative model, thereby reinforcing our conclusion. 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.

Figure B.10: IRF of hours worked to the world non-technology shock



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

In parallel with Table 3.1, Table B.2 summarizes the share of variance in labor input explained by the permanent technology shock in advanced and developing economies using the alternative VAR model. Consistent with the panel VAR evidence, the technology shock is an important driver of dynamics of hours worked in advanced economies (second column), while labor market dynamics in developing economies are dominantly driven by the non-technology shock (fifth column). This finding is robust to (i) using a group-specific technology shock (third and sixth columns) and (ii) using employment instead of hours worked in the VAR model (fourth and seventh columns).

Table B.2: Share of variation in labor input explained by the permanent technology shock (%)

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

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

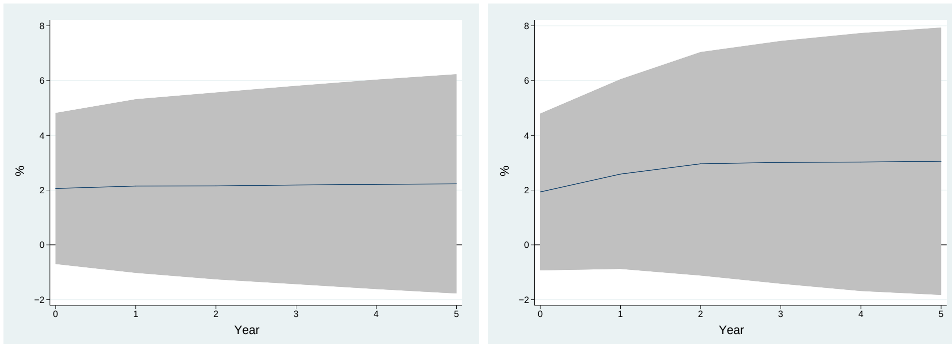
Response of real consumption to the permanent technology shock. As in the panel VAR model, we estimate a trivariate VAR model augmented with real consumption at the group level as a third variable in the VAR system. In doing so, we replace $Y_t = (\Delta z_t^h, \Delta h_t)'$ in equation (3.3) with $Y_t = (\Delta z_t^h, \Delta h_t, \Delta c_t)'$, where Δc_t is the annual growth in real consumption aggregated at the group level. We aggregate real consumption across countries in each group, similar 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 $A_{12}(1) = A_{13}(1) = A_{23}(1) = 0$.[30]

Figure B.11 compares the response of consumption to the world technology shock between advanced and developing economies. Unlike the response of labor input, the magnitude of the consumption response in developing economies is no smaller than that in advanced economies, despite the wide confidence interval in both cases. This finding also corroborates the baseline findings using the panel

[30] 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.

VAR model.

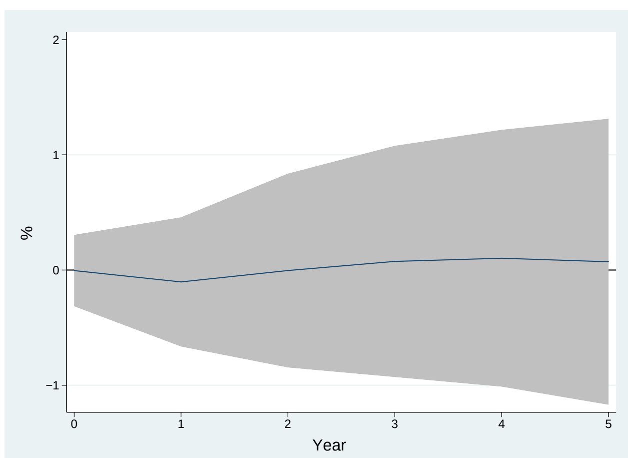
Figure B.11: IRF of consumption to the world technology shock



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

As in the case of the panel VAR model, the response of hours worked to the world permanent technology shock using the aggregate VAR model is also muted in advanced economies during the period in which subsistence consumption is likely to matter (Figure B.12).

Figure B.12: IRF of hours worked to the world permanent technology shock in advanced economies: 1950-1970

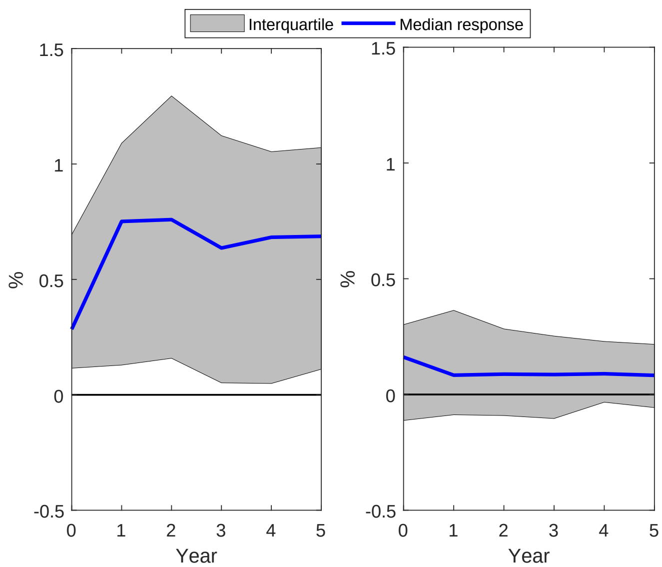


Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate VAR model of advanced economies ($\Delta z_t^{World,h}$, $\Delta h_t^{Advanced}$) and its 90% confidence interval from 500 bootstraps.

B.4 Country-by-country analysis

The response of labor input analyzed in the previous section uses aggregate-level labor input from each group. Following Dupaigne and Fève (2009), we also test the robustness of our findings by using country-level labor input instead. In other words, for each country i, $Y_{i,t}$ is defined as $(\Delta z_t^{World,h}, \Delta h_{i,t})'$. For each group of countries in the main sample, we compute the interquartile range of point estimates to summarize the results. Figure B.13 shows that of hours worked, and Figure B.14 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.[31]

Figure B.13: Country-by-country IRF of hours worked to the world permanent technology shock

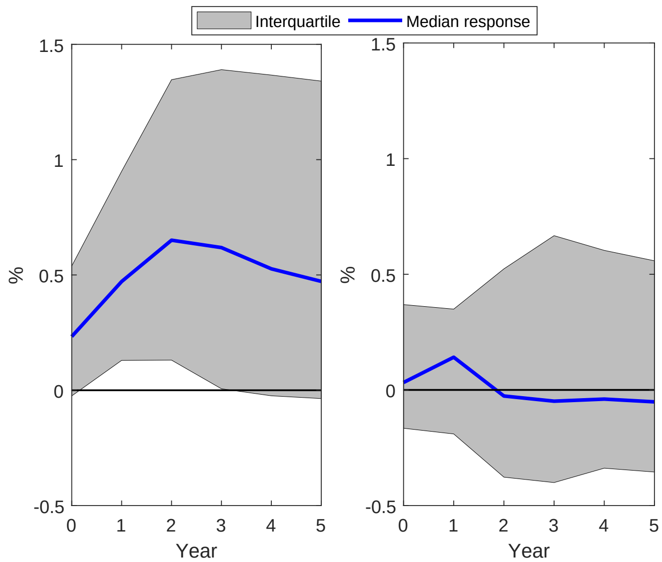


Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate aggregate VAR model $(\Delta z_t^{World,h}, \Delta h_{i,t})$. The left panel shows the interquartile distribution of advanced economies and the right panel shows the interquartile 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 B.15 compares this weighted response using country-level labor input with the previous response

[31] 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 B.14: Country-by-country IRF of employment to the world permanent technology shock



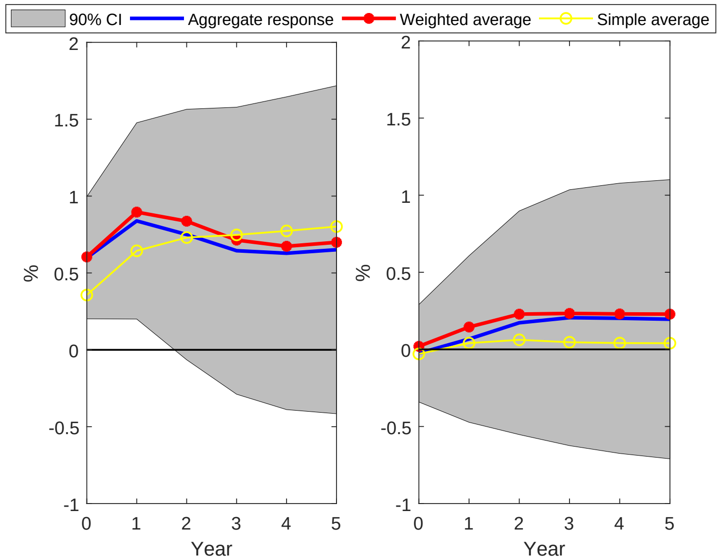
Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate aggregate VAR model $(\Delta z_t^{World,n}, \Delta n_{i,t})$. The left panel shows the interquartile distribution of advanced economies and the right panel shows the interquartile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

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.

To account for idiosyncratic productivity shocks explicitly, 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 Figure B.16, 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.

Lastly, we compare the size of the impact response of labor input to the technology shock obtained from country-by-country VAR analysis to the proxy of subsistence consumption across countries. Figure B.17 confirms that per-capita income also explains the cross-country heterogeneity in the response of hours worked (left panel) and employment (right panel) to the permanent technology shock from the

Figure B.15: Average IRF of hours worked to the world permanent technology shock

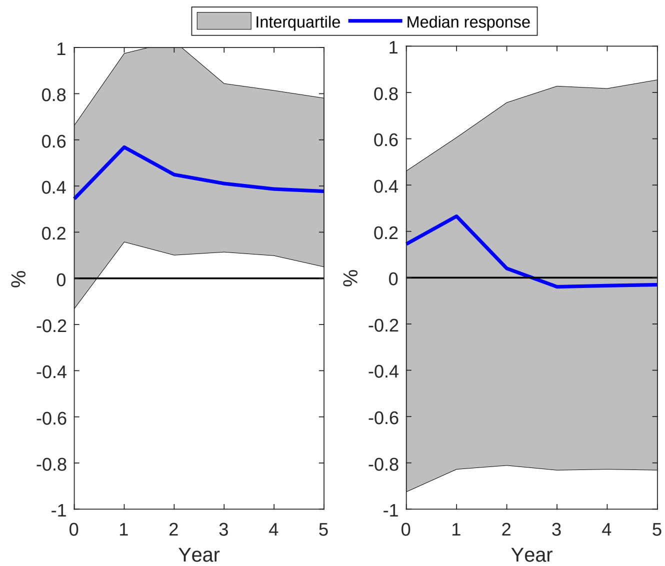


Note: This figure displays the impulse response function of hours worked to the permanent world technology shock in a bivariate aggregate VAR model ($\Delta z_t^{World,h}, \Delta h_{i,t}$). The left panel shows the average of the country-by-country responses of advanced economies and the right panel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

alternative VAR model.[32] The correlation is 0.28 and 0.25, and the associated p-value is 0.06 and 0.02, respectively. Taken together, the subsistence consumption channel can explain the differences in both unconditional and conditional moments of hours worked and employment across countries.

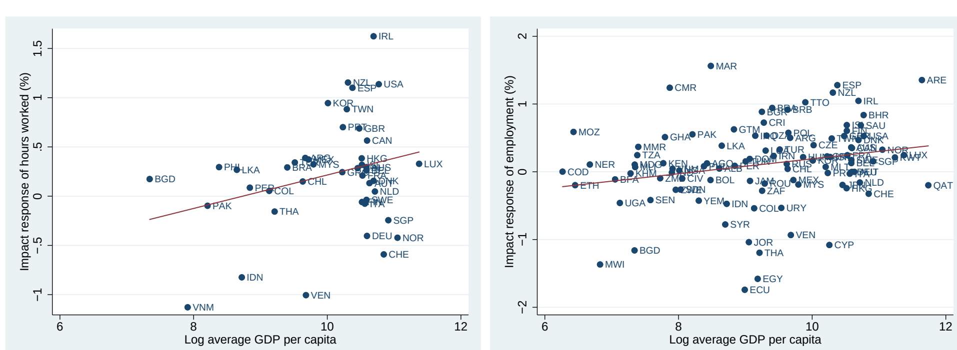
[32]The results using the size of the informal sector or the share of agriculture are qualitatively similar and available upon request.

Figure B.16: 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 aggregate 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.

Figure B.17: 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 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 B.4.

C 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.

C.1 New Keynesian model with nominal price rigidities

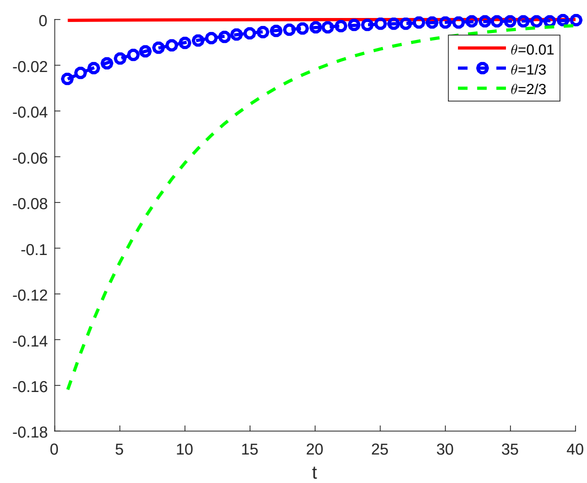
The first natural candidate to explain our empirical findings is the degree of price rigidities. As the negative response of hours worked to the permanent technology shock in Galí (1999) advocates an explanation based on a class of new Keynesian models with nominal price rigidities, one might argue that 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 C.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.[33]

[33] 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 C.1: Response of hours worked to a technology shock: New Keynesian model with varying nominal price rigidities



C.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.[34]

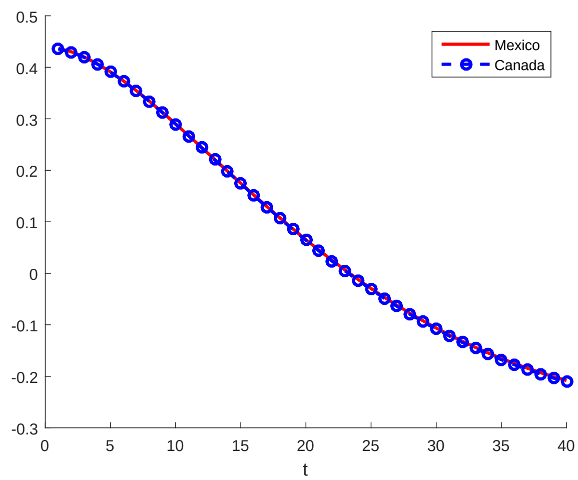
In their paper, two countries representing each group of countries are compared; Canada and Mexico. We use their model to obtain the IRFs of hours worked to the technology shock for each country and report them in Figure C.2.[35] It is clear that the model with a trend shock cannot reproduce different

[34]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.

[35]For this exercise, we extend the Dynare code kindly shared by Johannes Pfeifer and confirm that the model economy

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



C.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)). To check this possibility, we consider a version of Iacoviello (2015)'s model.[36]

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

simulated from the code successfully replicates the key figures and tables in Aguiar and Gopinath (2007).

[36] 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.

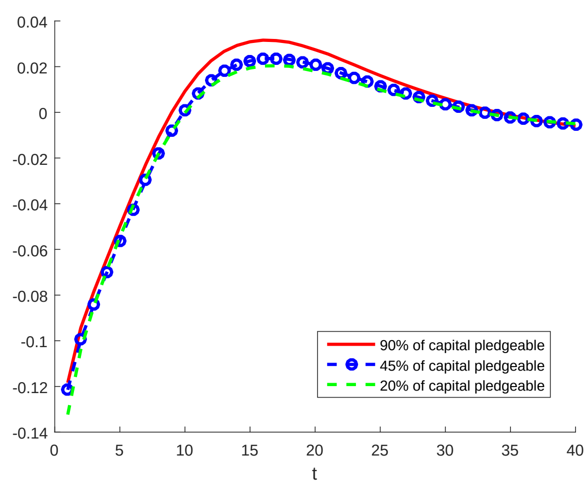
borrowing constraints for the entrepreneur (the producer in this economy):

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

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.[37] 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 C.3.

Figure C.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, even when we impose unrealistically tight borrowing constraints.[38] 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

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

[38]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.

productivity shock cannot induce a large enough income effect, which is necessary to dampen the response of hours worked to the technology shock.