Supplementary Appendix to "Financial Development and Long-Run Volatility Trends"

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This file contains two appendices to the paper. Appendix A (also called Appendix V in the text) provides data descriptions and reports model-implied moments for the Bayesian estimation presented in Section 7. Appendix B (also called Appendix VI in the text) presents additional robustness analyses for our model.

1 Appendix A: Bayesian Estimation for OECD Countries

1.1 Aggregate Data for the U.S.

The aggregate time series used in constructing the four observables in the Bayesian estimation are defined below. All time series are quarterly data (1975Q1-2014Q4). All series are downloaded from https://fred.stlouisfed.org.

1. Real Gross Domestic Product, billions of chained 2009 dollars, seasonally adjusted annual rate.
2. Personal Consumption Expenditure on Nondurable Goods, billions of chained 2009 dollars, seasonally adjusted annual rate.
3. Personal Consumption Expenditure on Services, billions of chained 2009 dollars, seasonally adjusted annual rate.
4. Real Gross Private Domestic Investment, billions of chained 2009 dollars, seasonally adjusted annual rate.
5. Hours of All Persons in Nonfarm Business Sector, 2009=100, seasonally adjusted.

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6. Civilian Noninstitutional Population Over 16, thousands of persons.
7. Relative Price of Investment Goods Index, 2009=1, seasonally adjusted. This series is calculated as investment divided by consumption deflator, see more details at https://fred.stlouisfed.org/series/PIRIC.
8. Real GDP per capita = (1)/(6).
9. Real Consumption per capita = [(2)+(3)]/(6).
10. Real Investment per capita = (4)/(7)/(6).
11. Hours worked = (5)/(6).

1.2 Aggregate Data for Other OECD Countries

1. Growth Rate of Gross Domestic Product, expenditure approach, growth rate compared to previous quarter, seasonally adjusted.
2. Growth Rate of Private Final Consumption Expenditure, growth rate compared to previous quarter, seasonally adjusted.
3. Growth Rate of Gross Fixed Capital Formation, growth rate compared to previous quarter, seasonally adjusted.
4. Population Ages 15 to 64, thousands of persons.
5. For some of the OECD countries, we use Weekly Hours Worked for Manufacturing as a proxy of hours worked. For those countries that hours worked is not available, we use Employed Population: Aged 15 and Over as a proxy. The above series are in quarterly frequency and seasonally adjusted.
6. Growth Rate of Real GDP per capita = (1) – growth rate of (4).
7. Growth Rate of Real Consumption per capita = (2) – growth rate of (4).
8. Growth Rate of Real Investment per capita = (3) – growth rate of (4) – growth rate of U.S. Relative Price of Investment Goods Index.
9. Growth Rate of Hours worked = growth rate of (5).

   All the growth rate series are demeaned from its sample average. The time series (1)-(3) are downloaded from OECD website: http://stats.oecd.org/. The time series (4) and (5) are downloaded from https://fred.stlouisfed.org.

Table A.1 below gives a summary of the data used for OECD countries.

Table A.1 Data summary of OECD countries

Country Name	Coverage	Hours Worked Series	Avg. $\frac{G}{Y}$	Rel. $\frac{\text{Domestic Credit}}{\text{GDP}}$
Australian (AUS)	1975Q1-2008Q4	Weekly Hours Worked: Manufacturing	0.18	0.49
Austria (AUT)	1975Q1-2007Q4	Monthly Hours Worked: Industry Excluding Construction	0.19	0.61
Belgium (BEL)	1983Q3-2014Q4	Weekly Hours Worked: Manufacturing	0.23	0.57
Canada (CAN)	1975Q1-2013Q4	Weekly Hours Worked: Manufacturing	0.21	0.72
Chile (CHL)	1995Q1-2013Q4	Weekly Hours Worked: Manufacturing	0.12	0.40
Czech (CZE)	1994Q1-2014Q4	Employed Population: Ages 15+	0.20	0.27
Germany (DEU)	1975Q1-2006Q4	Weekly Hours Worked: Manufacturing	0.19	0.67
Denmark (DNK)	1990Q1-2013Q4	Employed Population: Ages 15+	0.25	0.90
Estonia (EST)	2000Q2-2014Q4	Employed Population: Ages 15+	0.18	0.17
Finland (FIN)	1975Q1-2014Q4	Employed Population: Ages 15+	0.21	0.46
France (FRA)	2003Q2-2014Q4	Employed Population: Ages 15+	0.23	0.57
U.K. (GBR)	1999Q3-2014Q4	Employed Population: Ages 15+	0.20	0.75
Greece (GRC)	1998Q1-2014Q4	Employed Population: Ages 15+	0.20	0.50
Hungary (HUN)	1995Q2-2014Q4	Monthly Hours Worked: Manufacturing	0.22	0.31
Israel (ISR)	1995Q2-2014Q4	Employed Population: Ages 15+	0.24	0.93
Ireland (IRL)	1975Q1-2007Q4	Weekly Hours Worked: Manufacturing	0.18	0.53
Italy (ITA)	1998Q2-2014Q4	Employed Population: Ages 15+	0.19	0.58
Japan (JPN)	1975Q1-2014Q3	Weekly Hours Worked: Manufacturing	0.16	1.57
Korea (KOR)	1983Q2-2014Q4	Employed Population: Ages 15+	0.12	0.46
Luxemburg (LUX)	1980Q2-2014Q4	Monthly Hours Worked: Manufacturing	0.16	0.67
Mexico (MEX)	1980Q2-2014Q4	Monthly Hours Worked: Manufacturing	0.11	0.25
Netherland (NLD)	2000Q2-2014Q4	Employed Population: Ages 15+	0.24	0.83
New Zealand (NZL)	1987Q3-2014Q4	Employed Population: Ages 15+	0.18	0.55
Norway (NOR)	1988Q3-2008Q4	Weekly Hours Worked: Manufacturing	0.20	0.39
Poland (POL)	2000Q2-2014Q4	Employed Population: Ages 15+	0.18	0.23
Portugal (PRT)	1998Q2-2014Q4	Employed Population: Ages 15+	0.20	0.73
Slovak (SVK)	1999Q2-2014Q4	Employed Population: Ages 15+	0.19	0.22
Slovenia (SVN)	1999Q2-2014Q4	Employed Population: Ages 15+	0.19	0.23
Sweden (SWE)	1987Q2-2014Q4	Employed Population: Ages 15+	0.25	0.41
Turkey (TUR)	1977Q2-2014Q4	Employed Population: Ages 15+	0.11	0.24

Note: Latvia and Switzerland are excluded from the estimation due to the short series of hours worked observations. The Avg. $\frac{G}{Y}$ is computed as the average value of annual general government final consumption expenditure as percentage of GDP. The $\frac{\text{Domestic credit}}{\text{GDP}}$ is the "Domestic credit provided by financial sector as percentage of GDP". We compute the average relative ratio to that in U.S. over sample periods. The above two series are downloaded from WDI.

1.3 Model-Implied Moments

The table below reports the business cycle moments according to Table 1 in Aguiar and Gopinath (2007). In particular, the Table A.2 compares the model generated moments with those in the actual data when FD is calibrated/estimated accordingly. We compute the moments for both U.S. and OECD countries. Our results are indeed consistent with the empirical observation that countries with relatively less developed financial markets tend to have higher consumption volatility relative to GDP. More specifically, OECD countries have lower FD and higher consumption volatility relative to GDP, both in the data and in the model.

Table A.2 Business cycle moments: Model v.s. Data

	U.S.		OECD	
	Model	Data	Model	Data
$\sigma\left(Y\right)$	0.0117	0.0152	0.0166	0.0178
$\sigma(\Delta Y)$	0.0089	0.0077	0.0126	0.0104
$\rho\left(Y\right)$	0.7109	0.8722	0.7115	0.8160
$\rho\left(\Delta Y\right)$	-0.0881	0.1799	-0.0935	0.1308
$\sigma\left(C\right)/\sigma\left(Y\right)$	0.6625	0.5584	0.9676	0.9292
$\sigma\left(I\right)/\sigma\left(Y\right)$	2.3694	3.3201	2.6661	3.0795
$\rho\left(C,Y\right)$	0.2640	0.8410	0.4636	0.7056
$\rho\left(I,Y\right)$	0.9132	0.8828	0.7935	0.7543

Note: We follow Aguiar and Gopinath (2007) to filter the time series (model generated or actual data) by using HP filter with smoothing parameter of 1600. The moments for U.S. economy are computed based on the simulation with estimation parameters evaluated at posterior mode. The moments reported for OECD countries are average values of moments simulated for each OECD country. The simulation is conducted with parameters evaluated at posterior mode.

In addition, our model is able to reproduce the feature that consumption is more volatile than output in developing countries. In Table A.3, we report the model-simulated relative volatility between consumption and output for OECD countries. We also compare the simulated results with that in the data. From the table, it can be seen that our simulated $\frac{std(C)}{std(Y)}$ can broadly match the data counterpart, especially for those countries with $\frac{std(C)}{std(Y)} > 1$.

Table A.3 Relative consumption volatility: model v.s. data

	Model	Data		Model	Data
AUS	0.85	0.86	ISR	0.96	1.31
AUT	1.08	1.27	ITA	0.73	1.14
BEL	0.65	0.79	JPN	0.81	1.39
CAN	0.76	0.96	KOR	1.36	1.18
CHL	1.22	0.91	LUX	0.56	0.60
CZE	0.74	0.98	MEX	1.21	1.00
DEU	0.84	1.07	NLD	0.58	0.70
DNK	1.00	0.94	NOR	1.01	0.79
ESP	1.15	1.28	NZL	1.10	0.89
EST	1.06	0.95	POL	0.80	0.79
FIN	0.84	1.11	PRT	1.25	0.88
FRA	0.51	0.94	SVK	0.69	0.58
GBR	0.91	0.61	SVN	0.57	0.89
GRC	1.14	0.80	SWE	0.89	1.10
HUN	1.24	1.25	TUR	1.15	1.06
IRL	1.15	0.98	USA	0.56	0.66

Note: This table reports the relative volatility between consumption and output. In particular, we follow Aguiar and Gopinath (2007) to compute the standard deviation of HP filtered (with smooth parameter 1600) consumption and output. The relative volatility is defined as $\frac{\text{std(C)}}{\text{std(Y)}}$.

1.4 Sensitivity of Prior of θ

The model's prediction of the output volatility may be primarily affected by the setup of the country-specific prior of θ. To address this concern, we first compare the prior and the posterior of the parameter θ for 31 OECD countries in our cross-country analysis. The results show that for most of the sample countries (except for Czech and Korea) the posteriors of the θ largely deviate from the priors.[1] In particular, for most of the countries the dispersion of the posterior is significantly less than that of the prior. This indicates that the sensitivity of posterior mean regarding the prior mean is low (Muller, 2012).

Secondly, we conduct another robustness analysis by setting a common prior of θ across all countries without the country-specific adjustment in Section 7. We then compute the model-implied output volatilities and compare them with those in the real data. The Figure below shows that the model-implied output volatilities present very similar pattern to the one in Figure 8 in the main text. This indicates that the variations in the simulated output volatilities are not mainly driven by the country-specific priors of θ.

[1] The detailed results are available upon request.

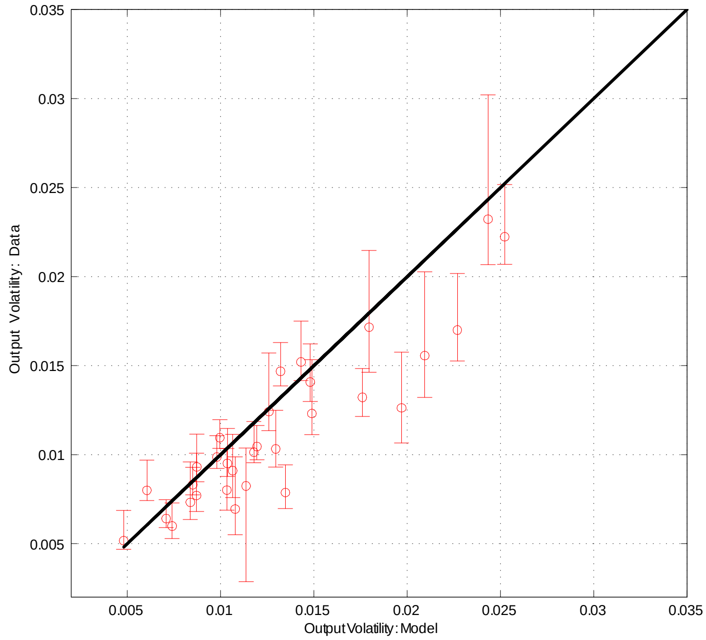

Figure A.1 Output volatility: model v.s. data, common prior of θ

Note: The model-implied output volatility is the theoretical standard deviation of output growth rate in the model. The vertical bar indicates 95% quantile based on 100,000 simulations under the posterior draws of estimated parameters. The output volatility for the data is the sample standard deviation of output growth over time.

2 Appendix B: Other Robustness Analyses

2.1 Alternative Financial Development Index

In addition to the three measures of financial development, here we also use credit to non-financial corporations as % of GDP from BIS dataset as an indicator for financial development. The BIS dataset covers following economies: Argentina, Austria, Australia, Belgium, Brazil, Canada, Switzerland, Chile, China, Czech, Germany, Denmark, Spain, Finland, France, UK, Greece, HK, Hungary, Indonesia, Ireland, Israel, India, Italy, Japan, Luxembourg, Korea, Mexico, Malaysia, Netherlands, Norway, New Zealand, Poland, Portugal, Russia, Saudi Arab, Sweden, Singapore, Thailand, Turkey and US. The correlation between it and output volatility is negative around -0.46. The L-shaped relation remains the same as that in the baseline analysis. Figure B.1 plots the result.

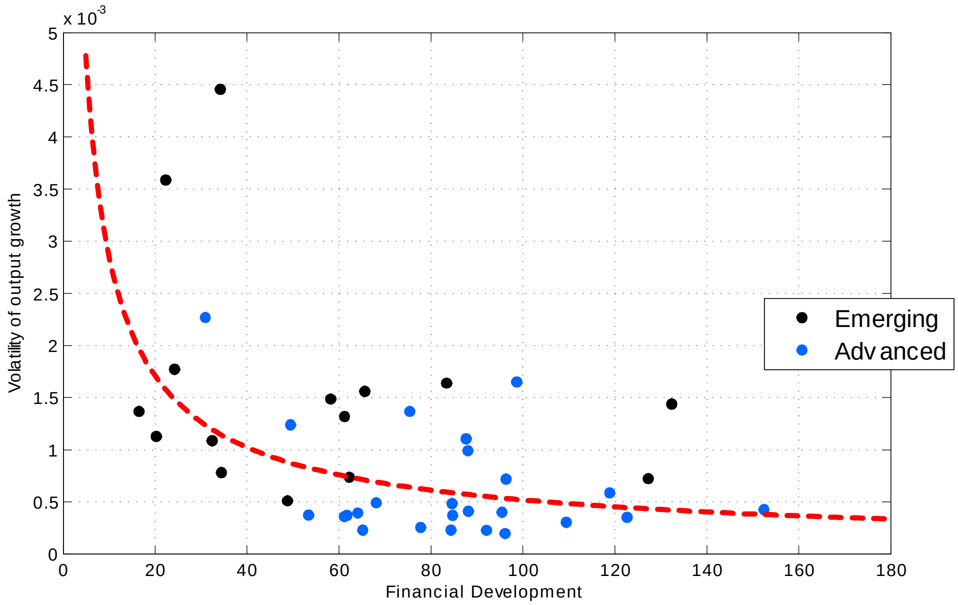

Figure B.1 Financial development and output volatility: alternative FD index

2.2 Financial Liberalization and Output Volatility

To document the impact of financial liberalization on output volatility, we use "financial liberalization index" constructed by Kaminsky and Schmukler (2008), which captures change in financial regimes and indicates the level of financial liberalization in a nation. The financial liberalization index has three sub-indices: Domestic Financial Sector Liberalization Index, Capital Account Liberalization Index and Stock Market Liberalization Index. The dataset covers for 28 economies.[2] The value for each index (Domestic Financial Sector, Capital Account, and Stock Market) is presented for each country, 1 indicating the most liberalized and 3 the least liberalized. We compute the average value of the three indices for each country over time. The correlation between so constructed financial liberalization variable and output volatility is significantly positive at around 0.6, indicating that more financially liberalized economies tend to be less volatile. Figure B.2 plots the result.

[2] The covered economies are: Argentina, Brazil, Canada, Chile, Colombia, Denmark, Finland, France, Germany, Hong Kong, Indonesia, Ireland, Italy, Korea, Malaysia, Mexico, Norway, Peru, Portugal, Spain, Sweden, Thailand, UK, United States, Venezuela.

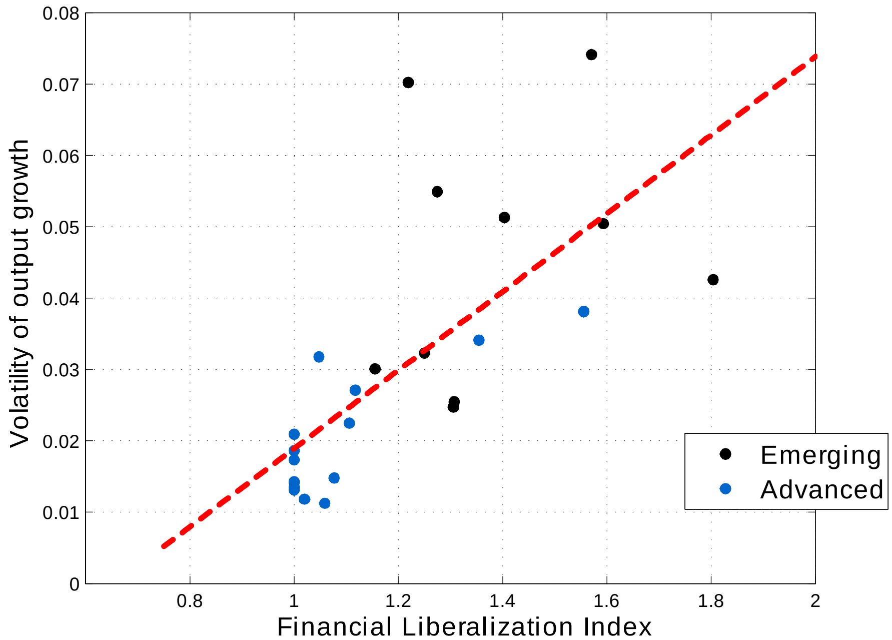

Figure B.2 Financial liberalization and output volatility

2.3 Semiparametric Regression

In addition to the materials presented in Appendix IV, we present the following results, based on Robinson's (1988) semiparametric regression method to estimate the relation between output volatility and financial development measures while controlling for other important factors. The sample size (number of countries) in this analysis is smaller because of the additional data variables we added to the control variable list. In particular, consider the following regression:

$$\sigma_{g,i} = \beta_0 + f(FD_i) + \beta' X_i + \varepsilon_i,\ i = 1, 2, ..., N \tag{B.1}$$

where σ_g is the standard deviation of GDP growth rate, FD denotes the level of financial development, which enters nonparametrically in the equation, X denotes a vector of explanatory variables including: the mean of trade openness (defined as export and import to GDP ratio) and the standard deviation of terms of trade are used to capture, respectively, the openness of the goods market and the size of shocks from foreign goods market; both the mean and the standard deviation of capital flows (defined as inflows and outflows to GDP ratio) reflect, respectively, the openness of the financial account and the size of shocks from the international capital market; the standard deviation of money growth and the standard deviation of the fiscal expenditure to GDP ratio are used to capture the policy volatility; the mean of relative income is used to capture the size of economy; the mean and the standard deviation of the percentage change of exchange rate are used to capture the exchange rate regimes.

Table B.1 Regression of growth volatility: parametric part

	OLS	Semipar
FD^{-2}	33.504**	–
	(16.152)	–
trade openness	0.448	0.535
	(0.281)	(0.442)
capital flows	0.064***	0.052
	(0.029)	(0.043)
s.d. capital flows	-0.744***	-0.660
	(0.350)	(0.499)
relative income	-0.176	-0.227
	(0.144)	(0.438)
s.d. terms of trade	-0.006	0.006
	(0.036)	(0.027)
s.d. M2/GDP	0.021	0.028
	(0.017)	(0.027)
fiscal policy volatility	51.260***	50.367***
	(13.881)	(11.815)
Δexchange rate	-0.599	-0.155
	(1.143)	(1.108)
s.d. Δexchange rate	-0.112	-0.097
	(0.283)	(0.329)
R^2	.46	.34
num of observation	77	76

Note: FD represents financial development, defined as the private credit-to-GDP ratio. Trade openness is defined as the export and import to GDP ratio. Capital flow is the inflows and outflows to GDP ratio. Relative income is defined as domestic real output per capita relative to that in US. Fiscal policy is the fiscal expenditure to GDP ratio. Exchange rate is the ratio between domestic currency and the US dollar. The nominal rate between the local currency and the U.S. dollar. The data is from Lane and Melissa Ferretti (2007).

The estimation procedure is as follows. We first use the semipar command in Stata to estimate the nonlinear relationship between output volatility and FD. This step gives the coefficients for the control variables (i.e., the parametric part), see the third column in Table B.1. We compute the dependent variable partialled out from the parametric fit. Then we use the fractional polynomial regression (fracpoly command in Stata) to select the scale of power function of the nonlinear relation. The Hardle and Mammen's (1993) test shows the power of -2 gives the best fit. The estimated coefficient is presented in the first row under FD^{-2}.

Table B.2 below shows the results of the parametric fit part, which indicates that the coefficient is highly significant. Figure B.3 plots the estimated financial development and output volatility after controlling for other factors. It is clear that L-shaped relationship found in our baseline analysis remains robust. For comparison purpose, we also report in the table the results from OLS method (second column in Table B.1). Notice that in the estimation we do not include the linear term of FD since the test suggests that the nonlinear relationship is best fitted by its power FD^{-2}.

Table B.2 Regression of growth volatility: nonparametric part

Dependent variables	Coefficient
FD^{-2}	0.004***
	(0.001)
No. of observations	77
Adj. R^2	0.14

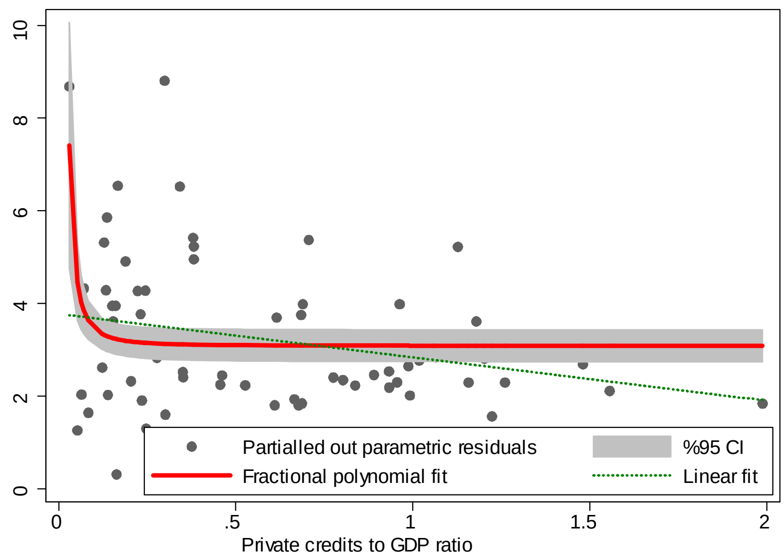

Figure B.3 Financial development and output volatility: Semiparametric estimation.

2.4 Simple Linear Regression

While the estimated non-linear trends are illustrative, it may be helpful to augment these results by estimating linear regressions on different samples (OECD v.s. less developed countries) and demonstrating that the regression coefficients are statistically different. Such estimates may provide a useful benchmark to evaluate the model-implied relationship between output volatility and financial development. Here we conduct linear regression for two subsamples: OECD countries and EMG-LDC countries (which include 44 emerging countries and 38 less developed countries), both subsamples are presented in Section 2 in the paper. The table below shows that the relation between financial development and output volatility is significantly negative for both subsamples; and in particular, the slope of the relationship is steeper for EMG-LDC economies than that for OECD countries. This pattern is robust to measures of financial development. In addition, to test whether the regression coefficients for OECD countries and EMG-LDC countries are significantly different, we conduct the Chow test. The lower panel in the table shows that for all three measures of FD used in Section 2 of the paper (columns 1 to 3 in the lower panel), we can reject the null hypothesis that the two groups of countries share the same value of coefficient at the 1% significance level.

Table B.3 Results of linear regressions

	OECD	EMG-LDC	OECD	EMG-LDC	OECD	EMG-LDC
FD1	-0.1127***	-0.2904**				
	(0.0304)	(0.1236)				
FD2			-0.0983***	-0.3633***		
			(0.0351)	(0.1260)		
FD3					-0.1052***	-0.3390***
					(0.0299)	(0.1120)
Cons.	17.7643***	35.5223***	14.2554***	34.7954***	15.5487***	34.1973***
	(3.6141)	(8.4910)	(3.4323)	(7.3289)	(3.2346)	(7.0523)
Obs.	30	82	30	82	30	82
Chow Test						
F Stat.	7.37		8.10		7.67	
p-value	0.0012		0.0006		0.0009	

2.5 Bayesian Estimation for Emerging Economies

2.5.1 Quantitative Results

Due to data availability, our paper only estimates the model for the OECD countries.[3] Here we estimate the baseline model for 16 emerging economies (which have all the macro data available to us). We use annual data from 1961 to 2014 (the following subsection provides more details about the data used in the estimation). Since some EMG countries are also OECD members and this estimation is based on annual data, the results presented here are thus not comparable to those based on OECD countries. We first estimate the U.S. economy based on the annual data as a benchmark. We calibrate the subjective discount rate β to be 0.96, depreciation rate δ to be 0.1, and use the same strategy to calibrate other deep parameters. For those parameter to be estimated, we use the same estimation procedure as that in the estimation of OECD countries with quarterly data. The table below reports the estimation results. The calibration values of $\{\beta, \delta, \sigma\}$ and the

[3] Many developing countries do not have aggregate hours worked data with long enough sample size to construct the variance of growth.

estimation (posterior mode) of η imply α =0.2665 and θ =0.2668.[4] For emerging economies, the calibration and estimation follow the same procedure as that used for OECD countries. Table B.4 below summarizes the posterior mode of estimated parameters for each emerging economy in the list.

Table B.4 Posterior mode for EMG economies: annual data

Country	θ	η	ρ_A	ρ_{Ω_c}	ρ_{Ω_n}	ρ_{Ω_G}	σ_A	σ_{Ω_c}	σ_{Ω_g}	σ_{Ω_n}	$\sigma_{\varepsilon}^{me}$
U.S.	0.2668	3.0022	0.8813	0.6981	0.8367	0.9903	0.0607	0.0570	0.0047	0.0279	0.0360
ARG	0.0373	3.5687	0.8698	0.3480	0.7598	0.5404	0.0919	0.0855	0.0320	0.0076	0.0177
BRA	0.1586	3.5374	0.9569	0.1098	0.4860	0.4270	0.0647	0.1147	0.0232	0.0105	0.0284
CHL	0.1104	3.4687	0.8734	0.1265	0.6026	0.6834	0.0908	0.2199	0.0212	0.3569	0.0205
COL	0.0630	3.5911	0.9275	0.1898	0.6923	0.9796	0.0798	0.0852	0.0176	0.0072	0.0360
HKG	0.2112	3.4503	0.9915	0.4019	0.8608	0.6765	0.0841	0.0964	0.0229	0.0149	0.0301
IDN	0.0709	3.4005	0.9890	0.1298	0.7026	0.5043	0.0956	0.1612	0.0336	0.0075	0.0428
IND	0.0774	3.5549	0.9575	0.0635	0.4842	0.4593	0.0458	0.0501	0.0127	0.0067	0.0205
ISR	0.1463	3.5737	0.7996	0.2843	0.7013	0.2740	0.0502	0.0811	0.0208	0.0159	0.0207
KOR	0.0969	3.7162	0.8955	0.3452	0.8366	0.5987	0.0860	0.1335	0.0403	0.0075	0.0275
MEX	0.0821	3.5091	0.9842	0.1360	0.8261	0.7247	0.1167	0.1212	0.0224	0.0068	0.0475
MYS	0.1738	3.5108	0.9690	0.4928	0.9011	0.4625	0.1321	0.1223	0.0300	0.0078	0.0425
PAK	0.1040	3.4846	0.9756	0.1290	0.6826	0.7828	0.0533	0.1020	0.0229	0.0076	0.0225
PER	0.0390	3.6528	0.8957	0.4182	0.8094	0.4220	0.1371	0.1694	0.0524	0.0194	0.0526
SGP	0.0822	3.6337	0.9554	0.3421	0.7201	0.4408	0.0857	0.1132	0.0335	0.0051	0.0309
THA	0.1307	3.5020	0.9178	0.3464	0.7204	0.8080	0.0930	0.0783	0.0049	0.0982	0.0527
VEN	0.1421	3.6256	0.9825	0.7460	0.8899	0.5060	0.0472	0.0687	0.0311	0.0162	0.0326

[4] The detailed posterior estimation results are available upon request.

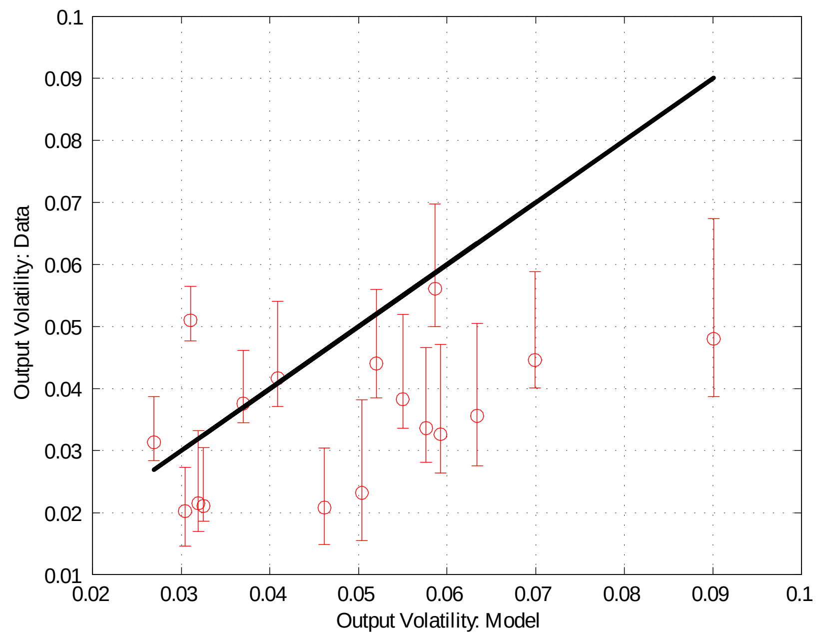

Figure B.4 Output volatility: model v.s. data, Emerging Economies

Note: The model-implied output volatility is the theoretical standard deviation of output growth rate in the model. The bar indicates the 95% quantile based on 100,000 simulations under the posterior draws of estimated parameters. The output volatility for the data is the sample standard deviation of output growth over time.

To see the model's fit, we compare the model-implied standard deviation of output growth with that in the data in Figure B.4. A point along the 45 degree line indicates a perfect fit. We can see from Figure B.4 that our model performs not too badly for these emerging economies in explaining their output volatility.

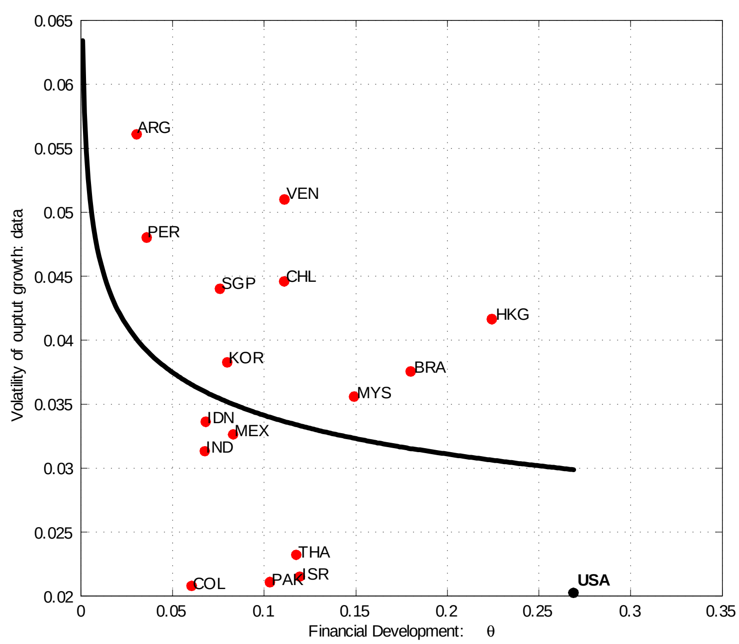

Figure B.5 Financial development (model) and output volatility (data).

Note: The output volatility is the standard deviation of output growth in the data; the financial development is indicated by the posterior mode of θ.

Figure B.5 plots the financial development parameter θ against the output volatility. It can be seen that a country with higher value of θ tends to have a lower output volatility. In particular, the L-shaped relationship for emerging economies is steeper than that for the OECD countries (see Figure 9 in the main text).

Suppose we set the value of financial development parameter θ in an emerging economy to the U.S. value and compute the corresponding changes in model-implied output volatility, we will see that this change is significantly negative. Table B.5 summarizes the main results. The column of "ΔVol" shows that when a country's financial system achieves the level of U.S. economy (more advanced than emerging economies), the volatility of aggregate output reduces remarkably.

Table B.5 Financial development and output volatility: EMG

	Standard Deviation of ΔY_t						
	Bench.	U.S. θ	ΔVol		Bench.	U.S. θ	ΔVol
ARG	0.0587	0.0542	-7.79%	KOR	0.0550	0.0515	-6.37%
BRA	0.0369	0.0354	-4.25%	MEX	0.0592	0.0552	-6.71%
CHL	0.0699	0.0644	-7.94%	MYS	0.0635	0.0613	-3.43%
COL	0.0462	0.0431	-6.73%	PAK	0.0325	0.0301	-7.29%
HKG	0.0409	0.0403	-1.42%	PER	0.0902	0.0831	-7.88%
IDN	0.0577	0.0524	-9.21%	SGP	0.0521	0.0488	-6.26%
IND	0.0269	0.0252	-6.38%	THA	0.0507	0.0485	-4.20%
ISR	0.0320	0.0308	-3.95%	VEN	0.0311	0.0297	-4.53%

2.5.2 Aggregate Data for Emerging Economies

The time series used in constructing the four observable variables in the Bayesian estimation for each emerging economy are listed below. All time series are in annual frequency. The coverage of time series varies across countries due to data availability.

1. Annual percentage growth rate of GDP per capita based on constant local currency. Aggregates are based on constant 2010 U.S. dollars. GDP per capita is gross domestic product divided by midyear population.

2. Annual percentage growth of household final consumption expenditure per capita, which is calculated using household final consumption expenditure in constant 2010 prices and World Bank population estimates.

3. Annual growth of gross fixed capital formation per capita based on constant local currency. Aggregates are based on constant 2010 U.S. dollars. The growth rate is adjusted by the growth rate of U.S. Relative Price of Investment Goods Index.

4. Annual growth of hours worked is the series Average Annual Hours Worked by Persons Engaged.

   All the growth rate series are demeaned from its sample average. The time series (1)-(3) are downloaded from World Bank website: http://data.worldbank.org/indicator. The time series (4) is downloaded from https://fred.stlouisfed.org.

Table below gives a summary of the data used for emerging economies.

Table B.6 Data summary of Emerging Economies

Country Name	Coverage	Avg. $\frac{G}{Y}$	Rel. $\frac{\text{Domestic Credit}}{\text{GDP}}$
Argentina (ARG)	1961-2014	0.11	0.14
Brazil (BRA)	1971-2014	0.15	0.48
Chile (CHL)	1961-2014	0.11	0.40
Colombia (COL)	1961-2014	0.12	0.24
Hong Kong (HKG)	1974-2014	0.07	0.77
Indonesia (IDN)	1971-2014	0.08	0.20
India (IND)	1972-2013	0.11	0.29
Israel (ISR)	1982-2014	0.28	0.61
Korea (KOR)	1961-2014	0.12	0.37
Mexico (MEX)	1961-2014	0.10	0.28
Malaysia (MYS)	1971-2014	0.14	0.64
Pakistan (PAK)	1961-2014	0.11	0.34
Peru (PER)	1971-2014	0.11	0.16
Singapore (SGP)	1961-2010	0.11	0.33
Thailand (THA)	1971-2014	0.13	0.60
Venezuela (VEN)	1961-2014	0.11	0.22

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