Technological Diversification

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Web Appendix

This Appendix is organized as follows. Section A presents supplementary evidence motivating the model. Section B collects the proofs. Section C studies the robustness of the numerical results to alternative parametrizations. Section D discusses several extensions.

A Supplementary Evidence

The presentation is organized as follows. Section A.1 elaborates and expands on the set of empirical observations presented in Section I. Specifically, using firm-level data for a wide range of countries at different stages of development, it presents novel evidence that i) firm-level volatility declines with the size of a firm and ii) firm-level and aggregate volatility comove positively. Section A.2 performs several robustness checks on the volatility-development relation. Section A.3 discusses evidence that firms grow by expanding the number of technologies and inputs used in production; it then studies evidence of diversification using input-output tables. Section A.4 studies the skewness of the distribution of growth rates. Section A.5 presents the samples of data used. Section A.6 concludes with an empirical illustration of the volatility-productivity relation using data on wheat production.

A.1 Empirical Observations

Empirical Observation 2: Firm-level volatility declines with the size of the firm.

In Section I we presented the results for the United States, using data from Compustat. In this section we note that this result appears to be present in all countries for which we have data.

Table $A1$ reports the results from cross-sectional regressions of (log) volatility (measured as before as the standard deviation of real sales growth) on (logged) size, where size is measured as either the number of employees or the volume of sales of the firm.

The data for Ghana, Kenya, and Nigeria come from the Center for the Study of African Economies (CSAE) comparative firm-level dataset; we use an unbalanced panel spanning the period 1992-2003 (see Rankin, Söderbom, and Teal, 2006). The data for all other countries come from ORBIS 2010 and correspond to an unbalanced panel from 2003 to 2007.

We also argued in the text that the volatility-size relationship does not appear to be driven entirely by diversification in output. In Table $A2$ we investigate this issue, by testing the robustness of the relation when we control for the number of business segments in which a firm operates. We also study the volatility-size correlation for firms that operate in a single business segment. The analysis is conducted for Compustat firms, an extend the results in Table 2 in the text. The number of business segments appears to positively (rather than negatively) relate to the volatility of firms. Single-segment firms do not appear to display different sensitivities to size. From this we conclude that output diversification cannot account for the decline in volatility with size. Our focus in the model is accordingly on the input side: bigger firms can resort to wider number of inputs to cope with shocks.

Table $A1$. Firm-Level Volatility and Size: Other Countries

Dependent Variable: Standard Deviation of Sales Growth Rates

	Austria		Belgium		Finland		France	
	Size Measure		Size Measure		Size Measure		Size Measure	
	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees
Size	-0.162***	-0.196***	-0.103***	-0.212***	-0.153***	-0.223***	-0.134***	-0.150***
	(0.0192)	(0.0222)	(0.00521)	(0.00613)	(0.00197)	(0.00327)	(0.000742)	(0.000998)
Constant	-2.327***	-2.328***	-2.304***	-2.071***	-2.097***	-1.969***	-2.493***	-2.505***
	(0.106)	(0.104)	(0.0231)	(0.0219)	(0.00387)	(0.00575)	(0.00151)	(0.00192)
Observations	1,376	1,264	14,702	13,649	86,233	70,756	780,966	662,216
R-squared	0.049	0.058	0.026	0.080	0.065	0.062	0.040	0.033

Dependent Variable: Standard Deviation of Sales Growth Rates

	Germany		Greece		Italy		Japan	
	Size Measure		Size Measure		Size Measure		Size Measure	
	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees
Size	-0.0818***	-0.181***	-0.175***	-0.160***	-0.119***	-0.136***	-0.235***	-0.206***
	(0.00322)	(0.00554)	(0.00393)	(0.00559)	(0.00104)	(0.00129)	(0.00736)	(0.00584)
Constant	-2.516***	-2.190***	-1.899***	-2.012***	-1.948***	-2.023***	-1.072***	0.0326
	(0.0146)	(0.0251)	(0.0108)	(0.0151)	(0.00252)	(0.00284)	(0.0218)	(0.0502)
Observations	35,398	20,805	29,144	22,356	487,964	382,681	8,965	8,969
R-squared	0.018	0.049	0.064	0.035	0.026	0.028	0.102	0.122

Table $A1$ continued.

Dependent Variable: Standard Deviation of Sales Growth Rates

	Korea		Netherlands		Portugal		Spain	
	Size Measure		Size Measure		Size Measure		Size Measure	
	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees
Size	-0.0511***	-0.135***	-0.115***	-0.184***	-0.108***	-0.162***	-0.115***	-0.167***
	(0.00168)	(0.00224)	(0.00681)	(0.00913)	(0.00137)	(0.00199)	(0.000878)	(0.00117)
Constant	-1.594***	-1.653***	-2.088***	-1.995***	-2.223***	-2.055***	-2.118***	-2.001***
	(0.0162)	(0.00595)	(0.0317)	(0.0321)	(0.00222)	(0.00353)	(0.00174)	(0.00242)
Observations	223,222	137,719	4,146	4,071	236,354	224,429	576,179	537,862
R-squared	0.004	0.026	0.065	0.091	0.026	0.029	0.029	0.036

Dependent Variable: Standard Deviation of Sales Growth Rates

	Sweden		Switzerland		Ghana		Kenya	
	Size Measure		Size Measure		Size Measure		Size Measure	
	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees	Volume of Sales	Number of Employees
Size	-0.212***	-0.288***	-0.128***	-0.132***	-0.185***	-0.188***	-0.170***	-0.245***
	(0.00125)	(0.00210)	(0.0267)	(0.0322)	(0.0356)	(0.0403)	(0.0488)	(0.0659)
Constant	-1.453***	-1.833***	-2.678***	-2.815***	-0.026	0.922***	-0.0515	1.559***
	(0.00439)	(0.00329)	(0.147)	(0.160)	(0.1310)	(0.3310)	(0.1870)	(0.5840)
Observations	205,578	187,104	487	381	213	213	187	187
R-squared	0.124	0.091	0.045	0.043	0.144	0.098	0.055	0.053

Dependent Variable: Standard Deviation of Sales Growth Rates

	Nigeria	
	Size Measure	
	Volume of Sales	Number of Employees
Size	-0.109***	-0.0811
	(0.0389)	(0.0651)
Constant	-0.934***	-0.592
	(0.1790)	(0.6260)
Observations	152	152
R-squared	0.035	0.01

Note: All variables are in logs. The equations for 0RBIS data countries use the 5-year standard deviation of annual (real) sales growth rates from 2002 to 2006 for developed countries. For Ghana, Kenya, and Nigeria, the unbalanced panel span 1992 to 2002 (see text). The two size measures (number of employees and volume of real sales) are computed at their mean values over the period. Robust standard errors in brackets. *Significant at 10%; **significant at 5%; *** significant at 1%.

Table $A2$. Firm-Level Volatility and Size.

Dependent Variable: Standard Deviation of Sales Growth Rates								
	Full Sample				Single-Segment Firms Sample			
	Size Measure				Size Measure			
	Number of Employees		Volume of Sales		Number of Employees		Volume of Sales	
Size	-0.250***	-0.161***	-0.228***	-0.201***	-0.266***	-0.150***	-0.251***	-0.193***
	[0.003]	[0.013]	[0.002]	[0.009]	[0.003]	[0.019]	[0.003]	[0.014]
Number of business segments	0.396***	0.400***	0.364***	0.418***				
	[0.010]	[0.021]	[0.009]	[0.017]				
Constant	-1.086***	-1.377***	-1.873***	-1.832***	-0.951***	-1.277***	-1.738***	-1.614***
	[0.028]	[0.082]	[0.019]	[0.036]	[0.034]	[0.107]	[0.028]	[0.052]
Firm-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	38,168	38,168	50,308	50,308	26,886	26,886	28,576	28,576
R-squared	0.279	0.723	0.278	0.688	0.277	0.767	0.300	0.765

Note: All variables are in logs. The equations use the 5-year standard deviation of annual (real) sales growth rates from 1975 to 2007. The two size measures (number of employees and volume of sales) are computed at their mean values over the lustrum. Year-fixed effects are included in all regressions. Clustered (by firm) standard errors in brackets. *Significant at 10%; **significant at 5%; *** significant at 1%.

Empirical Observation 3. Firm-level volatility and aggregate volatility tend to comove positively.

As said, this observation holds for the countries for which we have data and helps differentiate our paper from financial-diversification models that predict a negative comovement between micro and macro volatility. In the text, we discussed references supporting a positive comovement for the United States, France, and Germany.

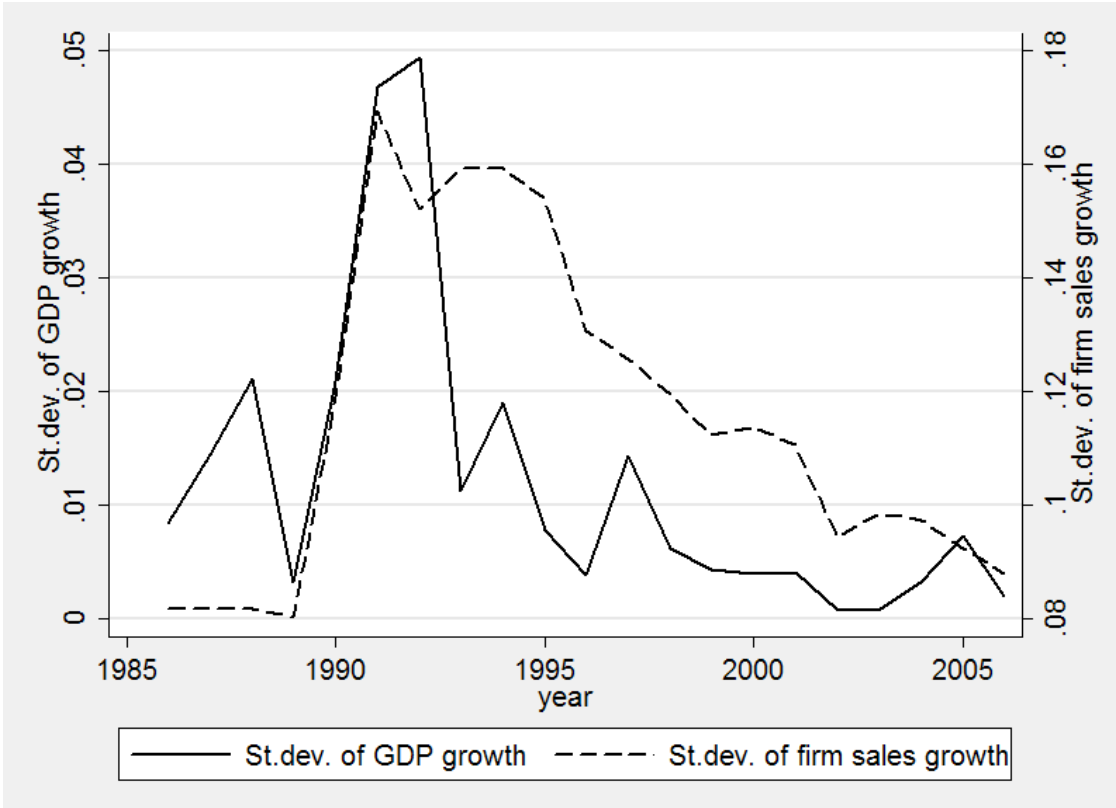
We also investigated volatility patterns for a relatively long panel of firm-level data for Hungary, uncovering a strong positive comovement between the volatility of firms' sales and aggregate GDP. The dataset is described in Halpern, Koren, and Szeidl (2010). The positive comovement is illustrated in Figure $A1$, which plots the volatility of the median firm, measured as the standard deviation of real sales growth and aggregate GDP volatility. The relation is evidently positive through most of the period.

In addition to these four countries, we analyzed a short panel of firm-level data for other 14 countries. The data for European countries as well as for Korea come from ORBIS and, although the period span is very short, it is possible—and informative—to explore whether firm and aggregate volatility have moved in the same direction over the available period. We therefore analyzed the change in volatility between 2002–2004 and 2005–2007 for privately owned firms.[71] The results indicate that during this period, 9 of the 11 countries saw a

[71] The dataset in principle starts in 2000 and ends in 2009, but the sample attrition at the beginning and end points (some countries have less than 1 percent of the firms at the beginning or end of the sample) renders the analysis unfeasible. For the Netherlands, the missing data problem is more severe, so we have to restrict the two periods, correspondingly, to 2003-2004 and 2005-2007. More information is available at request from the authors.

decline in aggregate volatility together with a decline in firm-level volatility. The exceptions are Greece and Italy, which experienced an increase in aggregate volatility together with a decline in firm-level volatility during this period.[72]

Figure $A1$. Firm-Level and Aggregate Volatility in Hungary



The data for Ghana, Kenya, and Nigeria come from CSAE's comparative firm-level dataset; the unbalanced panel spans the period 1992-2003, but the actual coverage varies across countries (see Rankin et al, 2006). We split the sample in two for all three countries, and computed the change in firm and GDP volatility before and after the mid-year in the sample for each country. In Ghana and Nigeria, firm-level and aggregate volatility moved in the same direction, while in Kenya, they moved in opposite directions. The data for African countries include listed firms, which in light of previous studies, tend to display negative comovement—so the data should be biased towards more negative comovement).

Considering all the information together (including the studies for the United States, Germany, France, and the results for Hungary), we find evidence that in 15 out of 18 countries (over 80 percent), firm-level and aggregate volatility appear to move in the same direction.

[72] One potential explanation for the divergence in trends in these two countries is that firm-level volatility does not take into account the exit of firms, which might have been important in 2007, and which should have contributed to higher firm-level volatility in the second period. In contrast, GDP volatility captures the volatility caused by firm exit.

Table $A3$. Change in Firm-Level and Aggregate Volatility

Country	Change in firm volatility	Change in GDP volatility
Austria	-66.51%	-47.30%
Belgium	-15.47%	-37.30%
Finland	-0.25%	-23.25%
Ghana	-25.78%	-44.07%
Greece	-4.80%	111.09%
Italy	-26.99%	49.75%
Kenya	-51.45%	26.43%
Korea	-1.96%	-30.70%
Netherlands	-7.00%	-24.00%
Nigeria	10.63%	101.59%
Portugal	-10.89%	-47.88%
Spain	-35.94%	-15.20%
Sweden	-4.64%	-31.07%
Switzerland	-47.66%	-57.83%

Notes: For non African countries, the table shows percentage changes in firm-level and GDP volatility between the periods 2002-2004 and 2005-2007 (for the Netherlands, due to missing data, the periods are 2003-2004 and 2005-2007). Firm-level volatility is measured as the standard deviation of real sales growth for the median firm over the 3-year periods (2-years for Netherlands). We correct for composition by calculating the volatility for a firm of the same size as the median firm in 2006. GDP volatility is standard deviation of GDP growth over the same periods for which firm volatility is computed. The data come from ORBIS 2010. For Kenya, Ghana, and Nigeria, the sample splitting dates and the overall length of periods studied are different. For each country, the sample is split in two in the intermediate year; this is 1998 for Ghana, 1996 for Kenya and 2000 for Nigeria. The data come from CSAE; see references in text. The sample period and splitting dates in the different datasets is strictly dictated by data availability.

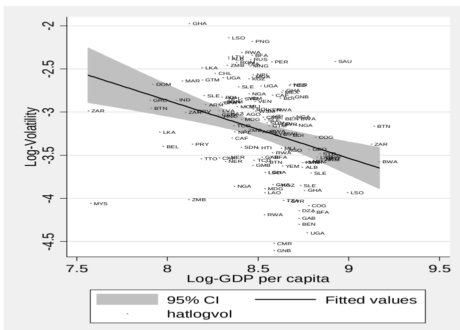
While we cannot be certain that firm and aggregate volatility also move together in other countries, we can study the relevance of the channel from another angle: models of financial diversification predict that financial development should play a key role in mediating the relation between volatility and development. In what follows, we first show graphically that the decline in volatility with development holds at different levels of financial development. Later on, we shall present a number of robustness checks showing that the negative relation between volatility and development is robust to a number of controls, including financial development.

The relationship between aggregate volatility and development holds at different levels of financial development, measured, as is standard, by the (log) ratio of private credit to

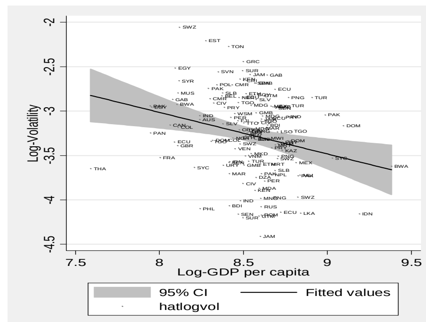
GDP.[73] This is illustrated in Figure $A2$, where we split the level of financial development into different quartiles. The graphs show that the decline of volatility with development is not sensitive to the level of financial development of the country. That is, controlling by financial development, there is still a strong negative association between volatility and development that needs explanation. (The data used for volatility are PPP-adjusted; the results are similar when non PPP-adjusted data are used.)

Figure $A2$: Volatility and Development by Financial Development Quartile

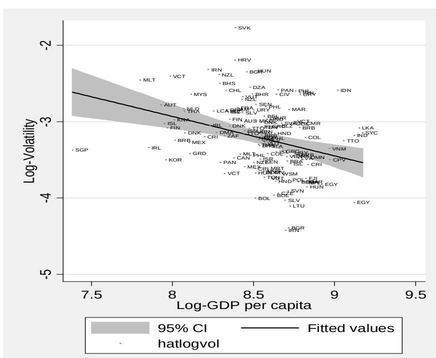
First Quartile



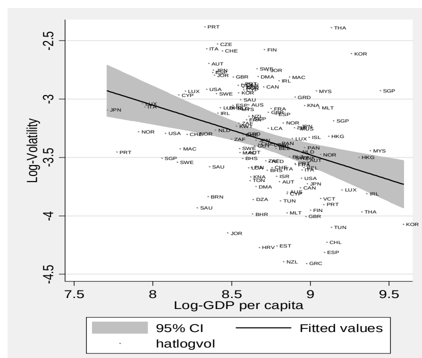
Second Quartile



Third Quartile



Fourth Quartile



Note: The plots show de-meaned (log) volatility (standard deviation of annual growth rates over non-overlapping decades from 1960 to 2007) against the average (log) real GDP per capita of the decade, for different quartiles of financial development. Regression lines and 95% intervals displayed.

A.2 Robustness of the volatility–development relationship

Table $A4$ extends the analysis in Table 1 and studies whether the correlation between volatility and development disappears or is weakened after controlling for measures of financial development, openness, war intensity, institutional constraints on the executive (which may capture the scope for political vulnerabilities), size of the government, policy variability (both monetary and fiscal). The regressions also inform on the association between volatility and financial development and its robustness to other controls. We should stress that many of

[73] Data come from the World Bank's *Financial Structure and Development Dataset v.4* (Finstructure) and correspond to the series private credit by deposit money banks and other financial institutions over GDP.

these covariates per se (such us those related to policy or political vulnerability) are often the consequence of underlying economic shocks, and are hence highly correlated with the level of development; this will play against finding any relation between volatility and development.

The dependent variable in all regressions is the (log) standard deviation of annual growth rates from 1960 through 2007.[74] All regressions include the average level of development as a regressor.

For reference, Column (1) reports the negative unconditional correlation between development and volatility, reproducing the second column of Table 1 (PPP-adjusted data). Column (2) and (3) control, respectively for financial development and the trade share of GDP. Column (4) includes these two regressors at the same time, and shows that financial development is no longer significant, while the trade share is significant at the 10-percent level (see Caselli, Koren, Lisicky and Tenreyro (2010) for a potential explanation for the negative association). In all cases, the level of development is strongly significant.

Columns (5) through (7) explore the role of wars and constraints on the executive (used as a proxy for institutional strength).[75] Column (8) includes all variables at the same time and the regression results indicate that only the level of development is significant.

Columns (9) and (10) control, incrementally, for the average level of government consumption over GDP and its standard deviation. The latter is positively correlated with volatility, consistent with Fatas and Mihov (2006)'s findings, but as before, the relation between volatility and per capita GDP is robust to its inclusion.[76] Columns (11) and (12) explore combinations of the joint role of openness, size of governments, and government expenditures' volatility. The latter is the only one that enters significantly in the equations. Columns (13) and (14) explore the association between GDP and terms of trade volatility, respectively excluding and including the trade share in the regressions. Fluctuations in terms of trade increase the overall volatility of GDP. Unfortunately, the data on terms of trade only start in 1980, and hence the sample is more than halved in these specifications. Still,

[74]Data on GDP come from the Penn World Table and are adjusted for PPP. Data on financial development come from the World Bank's Finstructure v.4 data set. Data on constraints on the executive come from Polity IV, data on wars come from the Major Episodes of Political Violence dataset. All other data come from the World Bank's World Development Indicators.

[75]Acemoglu et al (2003) have documented a negative association between this variable and volatility in a cross-section. They use the initial values of "constraints on the executive" (before the beginning of their sample), rather than the contemporaneous values of the variable, as we do here. Glaeser, La Porta, Lopez de Silanes, and Shleifer (2004), however, have shown that these indicators vary quite significantly over time and they should be viewed more as political outcomes than as "deep" institutional parameters. For that reason, we think it is more appropriate to use the contemporaneous values, since it allows us to better compare the regression coefficients of this variable with those of (contemporaneous) policy variables. In any event, the result that volatility and development are strongly correlated does not hinge on the period over which this variable is measured and, as it turns out, when controlling for country fixed effects, these variables do not have any explanatory power.

[76]Fatas and Mihov (2006) use shocks to government consumption rather than the actual measure of government consumption used here. Our results may be simply capturing the unanticipated component.

the relation between volatility and development is robust to the inclusion of this variable and the change in sample

Table $A4$. Volatility and Development. Robustness to Additional Controls

	Dependent variable: Standard deviation of annual GDP growth rates (log)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Real GDP per capita (log)	-0.496***	-0.422***	-0.468***	-0.418***	-0.516***	-0.520***	-0.514***	-0.425***	-0.492***	-0.426***	-0.469***
	[0.073]	[0.100]	[0.078]	[0.092]	[0.080]	[0.079]	[0.080]	[0.111]	[0.069]	[0.069]	[0.080]
Private credit relative to GDP (log)		-0.114*		-0.090				-0.098			
		[0.067]		[0.069]				[0.077]			
Trade share in GDP			-0.178	-0.291*				-0.257			-0.172
			[0.158]	[0.163]				[0.210]			[0.158]
Average war intensity					0.004		0.016	0.016			
					[0.029]		[0.027]	[0.030]			
Constraints on the executive						0.013	0.015	0.011			
						[0.020]	[0.020]	[0.023]			
Government share in GDP									1.215	-0.081	1.236*
									[0.739]	[0.688]	[0.730]
Volatility of government share in GDP										9.145***	
										[2.119]	
Terms of trade volatility											
Average inflation											
Inflation volatility											
Exchange rate volatility											
Constant	1.000	0.158	0.894	0.378	1.092	1.068	1.002	0.252	0.768	0.241	0.703
	[0.627]	[0.917]	[0.614]	[0.855]	[0.674]	[0.669]	[0.678]	[0.994]	[0.573]	[0.581]	[0.620]
Observations	706	550	673	541	579	580	576	460	663	662	655
Number of clusters	183	153	178	153	148	147	147	129	173	173	173

Note: The dependent variable is measured as the logged standard deviation of annual real GDP per capita growth rates over non-overlapping decades from 1960 to 2007 (source, PWT). The regressors are computed, correspondingly, as averages or standard deviations over the decade. Clustered (by country) standard errors in brackets. * Significant at 10%; ** significant at 5%; *** significant at 1%. The number of observations is determined by the availability of data from the PWT, WDI, Polity IV and Finstructure v4. Country-fixed effects included in all regressions. Note that the number of observations is significantly reduced when the variable terms-of-trade volatility is included.

Table $A4$ continued

	Dependent variable: Standard deviation of annual GDP growth rates (log)										
	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Real GDP per capita (log)	-0.407***	-0.447***	-0.409***	-0.461***	-0.425***	-0.400***	-0.387***	-0.397***	-0.397***	-0.422**	-0.365**
	[0.084]	[0.135]	[0.146]	[0.076]	[0.074]	[0.078]	[0.094]	[0.115]	[0.115]	[0.186]	[0.182]
Private credit relative to GDP (log)								-0.072	-0.072	-0.035	-0.053
								[0.088]	[0.088]	[0.103]	[0.101]
Trade share in GDP	-0.152		-0.273			-0.293*	-0.313	-0.242	-0.242	-0.210	-0.239
	[0.156]		[0.178]			[0.155]	[0.201]	[0.211]	[0.211]	[0.229]	[0.223]
Average war intensity							0.015	0.023	0.023	0.002	-0.002
							[0.028]	[0.031]	[0.031]	[0.033]	[0.034]
Constraints on the executive							0.024	0.026	0.026	0.028	0.030
							[0.023]	[0.026]	[0.026]	[0.024]	[0.024]
Government share in GDP	0.002					1.069	0.999	1.587	1.587	1.332	0.237
	[0.684]					[0.926]	[1.003]	[1.112]	[1.112]	[1.431]	[1.637]
Volatility of government share in GDP	8.835***										4.727
	[2.120]										[2.878]
Terms of trade volatility		2.124***	1.934***							1.807***	1.672**
		[0.630]	[0.633]							[0.677]	[0.649]
Average inflation				0.017*	0.138**	0.154**	0.218**	0.191	0.191	-0.139*	-0.123
				[0.009]	[0.058]	[0.075]	[0.090]	[0.148]	[0.148]	[0.080]	[0.079]
Inflation volatility					-0.058**	-0.064**	-0.084**	-0.058	-0.058	0.030	0.025
					[0.023]	[0.030]	[0.036]	[0.052]	[0.052]	[0.026]	[0.026]
Exchange rate volatility					0.231***	0.253***	0.229***	0.243	0.243	0.935**	0.848*
					[0.075]	[0.079]	[0.061]	[0.262]	[0.262]	[0.446]	[0.433]
Constant	0.182	0.242	0.146	0.661	0.313	0.151	-0.152	-0.338	-0.338	-0.329	-0.715
	[0.653]	[1.179]	[1.223]	[0.650]	[0.634]	[0.626]	[0.734]	[1.044]	[1.044]	[1.666]	[1.602]
Observations	654	330	326	593	586	563	476	437	437	252	252
Number of clusters	173	137	135	165	164	161	134	125	125	103	103

Note: The dependent variable is measured as the logged standard deviation of annual real GDP per capita growth rates over non-overlapping decades from 1960 to 2007 (source, PWT). The regressors are computed, correspondingly, as averages or standard deviations over the decade. Clustered (by country) standard errors in brackets. * Significant at 10%; ** significant at 5%; *** significant at 1%. The number of observations is determined by the availability of data from the PWT, WDI, Polity IV and Finstructure v4. Country-fixed effects included in all regressions. Note that the number of observations is significantly reduced when the variable terms-of-trade volatility is included.

Table $A5$. Volatility and Development. Robustness to Additional Controls (including Population)

	Dependent variable: Standard deviation of annual GDP growth rates (log)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Real GDP per capita (log)	-0.282***	-0.262***	-0.333***	-0.306***	-0.292***	-0.284***	-0.287***	-0.293***	-0.293***	-0.233***	-0.331***
	[0.086]	[0.094]	[0.080]	[0.083]	[0.088]	[0.089]	[0.090]	[0.096]	[0.074]	[0.074]	[0.080]
Population (log)	-0.577***	-0.528***	-0.586***	-0.522***	-0.575***	-0.576***	-0.574***	-0.580***	-0.557***	-0.548***	-0.574***
	[0.112]	[0.107]	[0.097]	[0.109]	[0.106]	[0.105]	[0.106]	[0.121]	[0.099]	[0.093]	[0.099]
Private credit relative to GDP (log)		-0.069		-0.058				-0.058			
		[0.061]		[0.061]				[0.068]			
Trade share in GDP			0.057	-0.091				-0.027			0.056
			[0.147]	[0.163]				[0.217]			[0.146]
Average war intensity					0.013		0.012	0.024			
					[0.027]		[0.027]	[0.030]			
Constraints on the executive						0.012	0.012	-0.012			
						[0.023]	[0.023]	[0.023]			
Government share in GDP									1.077*	-0.186	1.031*
									[0.606]	[0.572]	[0.607]
Volatility of government share in GDP										8.932***	
										[2.109]	
Terms of trade volatility											
Average inflation											
Inflation volatility											
Exchange rate volatility											
Constant	8.099***	7.081***	8.665***	7.459***	8.392***	8.304***	8.285***	8.453***	7.766***	7.129***	8.305***
	[1.567]	[1.808]	[1.414]	[1.774]	[1.514]	[1.517]	[1.528]	[2.014]	[1.402]	[1.329]	[1.425]
Observations	697	550	673	541	580	580	577	461	663	662	655
Number of clusters	181	153	178	153	148	147	147	129	173	173	173

Note: The dependent variable is measured as the logged standard deviation of annual real GDP per capita growth rates over non-overlapping decades from 1960 to 2007 (source, PWT). The regressors are computed, correspondingly, as averages or standard deviations over the decade. Clustered (by country) standard errors in brackets. * Significant at 10%; ** significant at 5%; *** significant at 1%. The number of observations is determined by the availability of data from the PWT, WDI, Polity IV and Finstructure v.4. Country fixed effect included in all regressions. Note that the number of observations is significantly reduced when the variable terms-of-trade volatility is included.

Table $A5$ continued.

	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Real GDP per capita (log)	-0.272***	-0.252*	-0.278*	-0.246***	-0.221***	-0.269***	-0.228**	-0.251***	-0.251***	-0.337***	-0.313**
	[0.083]	[0.133]	[0.143]	[0.080]	[0.078]	[0.077]	[0.092]	[0.093]	[0.093]	[0.128]	[0.128]
Population (log)	-0.564***	-1.044***	-1.066***	-0.562***	-0.545***	-0.527***	-0.543***	-0.592***	-0.592***	-1.047***	-1.036***
	[0.092]	[0.180]	[0.185]	[0.103]	[0.107]	[0.115]	[0.127]	[0.134]	[0.134]	[0.178]	[0.181]
Private credit relative to GDP (log)								-0.026	-0.026	-0.094	-0.100
								[0.078]	[0.078]	[0.086]	[0.084]
Trade share in GDP	0.074		-0.012			-0.069	-0.105	-0.048	-0.048	0.100	0.085
	[0.144]		[0.175]			[0.153]	[0.214]	[0.222]	[0.222]	[0.241]	[0.237]
Average war intensity							0.015	0.022	0.022	0.092**	0.091**
							[0.029]	[0.032]	[0.032]	[0.039]	[0.040]
Constraints on the executive							-0.014	-0.015	-0.015	-0.070***	-0.067***
							[0.021]	[0.023]	[0.023]	[0.021]	[0.021]
Government share in GDP	-0.168					0.977	0.915	1.081	1.081	-0.855	-1.294
	[0.567]					[0.760]	[0.860]	[0.999]	[0.999]	[1.185]	[1.358]
Volatility of government share in GDP	8.599***										1.997
	[1.999]										[2.365]
Terms of trade volatility		1.084**	1.022**							0.813*	0.756*
		[0.476]	[0.473]							[0.442]	[0.433]
Average inflation				0.027***	0.139**	0.169**	0.247**	0.217	0.217	-0.147**	-0.142*
				[0.009]	[0.065]	[0.079]	[0.106]	[0.182]	[0.182]	[0.074]	[0.074]
Inflation volatility					-0.054**	-0.067**	-0.091**	-0.069	-0.069	0.028	0.027
					[0.026]	[0.031]	[0.042]	[0.063]	[0.063]	[0.022]	[0.021]
Exchange rate volatility					0.234**	0.253**	0.196**	0.204	0.204	0.643*	0.613
					[0.094]	[0.097]	[0.077]	[0.346]	[0.346]	[0.380]	[0.380]
Constant	7.671***	15.318***	15.934***	7.598***	7.087***	7.108***	7.272***	8.138***	8.138***	16.514***	16.163***
	[1.365]	[2.797]	[2.962]	[1.516]	[1.569]	[1.663]	[1.879]	[2.224]	[2.224]	[3.163]	[3.181]
Observations	654	330	326	593	586	563	478	438	438	252	252
Number of clusters	173	137	135	165	164	161	135	125	125	102	102

Note: The dependent variable is measured as the logged standard deviation of annual real GDP per capita growth rates over non-overlapping decades from 1960 to 2007 (source, PWT). The regressors are computed, correspondingly, as averages or standard deviations over the decade. Clustered (by country) standard errors in brackets. * Significant at 10%; ** significant at 5%; *** significant at 1%. The number of observations is determined by the availability of data from the PWT, WDI, Polity IV and Finstructure v.4. Country fixed effect included in all regressions. Note that the number of observations is significantly reduced when the variable terms-of-trade volatility is included.

Columns (15) and (16) in Table $A4$, control, correspondingly, for the average level and, in addition (column 16), for the standard deviation of annual inflation rates, as well as for the standard deviation of exchange rate changes. As shown, the level of inflation and the exchange-rate volatility are both associated with an increase in volatility, and the association between volatility and development is virtually unaltered. Columns (17) through (22) present alternative specifications, to check if the results are robust to different combinations and different samples, where the variation in sample is entirely dictated by data availability. The last column (22) which includes all controls simultaneously, is based on a reduced sample (for which terms-of-trade variability is available).

In all regressions, the level of development shows a negative and statistically significant coefficient. Table $A5$ presents the same regressions as Table $A4$, controlling for the size of the population. Population enters significantly in all regressions, and while the coefficient on development is somewhat smaller, it is still statistically and economically significant. Financial development, in contrast, is insignificant in all specifications.

Finally, as we mentioned in the text, our model differs from standard financial diversification in what concerns the trade-off between productivity and volatility at the microeconomic level. This is largely motivated by Koren and Tenreyro (2007), who find a negative correlation between productivity and volatility within manufacturing sectors; developing countries tend to specialize in more volatile manufacturing sectors, which are on average less productive. In light of the model, it is also of relevance to study the differences in volatility and productivity between agriculture and manufacturing. To the extent that manufacturing uses more complex production technologies than agriculture, the model predicts that manufacturing should be both more productive and less volatile than agriculture. This is indeed consistent with a strong regularity in the data: On average, volatility of value-added per worker in agriculture is around 50 percent higher than that in manufacturing. At the same time, value added per worker is around twice as high in manufacturing than in agriculture. These figures are computed from the OECD-STAN database. In Table $A6$ we report the summary statistics by country. The table shows the average of labour productivity in manufacturing relative to labour productivity in agriculture from 1970 through 2003 and the corresponding ratio of volatilities over the same period. In all countries, manufacturing is significantly more productive, as predicted by the model. Moreover, manufacturing is also less volatile, with the only exception of Italy, where volatility is very similar in both sectors.

Table $A6$. Productivity and Volatility in Manufacturing Relative to Agriculture

Country	Relative Productivity in Manufacturing	Relative Volatility in Manufacturing
Australia	1.406	0.198
Austria	6.818	0.421
Belgium	2.076	0.447
Canada	1.717	0.467
Denmark	1.190	0.363
Finland	2.171	0.843
France	1.656	0.311
Germany	2.339	0.425
Greece	1.577	0.968
Italy	1.770	1.010
Japan	4.275	0.503
Korea	2.508	0.446
Luxembourg	1.779	0.351
Netherlands	1.372	0.366
Norway	1.542	0.727
Poland	4.225	0.362
Portugal	2.178	0.425
Spain	1.835	0.327
Sweden	1.462	0.650
United Kingdom	1.515	0.418
United States	2.239	0.233

Note: Column 2 shows the ratio of average labor productivity in manufacturing over labor productivity in agriculture from 1970 to 2003. Column 3 shows the corresponding ratio for standard deviation of labor productivity growth during the period.

A.3 Evidence of Technological Diversification

This section presents evidence that firms grow by expanding the set of technologies or inputs that they use. We start by reporting evidence on firms growth through the expansion in the set of technologies (broadly construed, as in the literature). We then turn to the expansion in inputs, by first documenting semi-anecdotal evidence on the adoption of new inputs and finally, by presenting evidence on the evolution on input-output matrices for a number of OECD countries; specifically, the input-output tables show that, in all countries, over the 1970-2005 period, most sectors in most countries have increased the usage of inputs from other sectors.

A.3.1 Technology diversification

Granstrand (1998) summarizes 5 main empirical findings on technological diversification (defined as the diversification in the set of technologies used by a firm). The findings are based on several studies of firms in Europe, Japan, and the United States, carried out in the period 1980–1994, altogether covering interviews, questionnaires and published data. The main interview and questionnaire study covered 14 Japanese large corporations (e.g., Hitachi, NEC, Toshiba, Canon, Toyota etc.), 20 European companies (e.g., Ericsson, Volvo, Siemens, Philips etc.), and 16 U.S. companies (e.g., IBM, GE, AT&T, GM, TI etc.) Analysis of published data covered 57 large OECD corporations.

In Granstrand's words *"major empirical findings of this project were as follows:*

"*1. Technology diversification at firm level, i.e., the firm's expansion of its technology base into a wider range of technologies, was an increasing and prevailing phenomenon in all three major industrialized regions, Europe, Japan and the US. This finding has also been corroborated by Patel and Pavitt (1994)."*

"*2. Technology diversification was a fundamental causal variable behind corporate growth. This was also true when controlled for product diversification and acquisitions."*

"*3. Technology diversification was also leading to growth of R&D expenditures, in turn leading to both increased demand for and increased supply of technology for external sourcing."*

"*4. Technology diversification and product diversification were strongly interlinked, often in a pull-push pattern in economically successful firms."*

"*5. The high-growth corporations followed a sequential diversification strategy, starting with technology diversification, followed by product and or market diversification. This result was independent of region and industry. "*

Granstrand (1998)'s goes on to say that technology diversification, being a central feature in the empirical findings, does not feature at all in received theories.

Granstrand, Patel and Pavitt (1997) provide additional case-study analysis of the phenomenon of technological diversification in the growth of a firm. They point out that technological diversification took place even in firms whose "product base" shrank (that is, product diversification declined), following an emphasis on "focus" and "back to basics during the

1980s in Europe and the US." These authors cite a number of examples of technological diversification. In their words: "*[t]hus, although still making the same product and contracting outcome of its production, Rolls-Royce has since the early 1970s substantially increased the range of technologies in which it is active, having exited only one field (piston engines). It has increasingly accumulated experience and knowledge in a variety of electronic-based technologies (e.g., censors, displays, simulations...)*"

"The case of Ericsson has been even more spectacular. Although external sourcing of technologies was important (and especially the co-operation with the lead user—Telia, which provides telephone services), new technological developments were sourced mainly in-house. During the period 1980-89, the total stock of engineers rose by 82%, and the diversity of competencies increased considerably. The traditional core competence in electrical engineering increased by only 32%, while mechanical engineering grew by 265%, physics by 124%, and chemistry by 44%... [T]echnology diversification and external technology acquisition took place in Ericsson's development of successive generations of cellular phones and telecommunications cables. The products became more multi-technology" and the company's technology base expanded. The new technological competencies that were required outnumbered the old ones that were made obsolete; and as a result of this process, "competence enhancement" dominated over "competence destruction" just as in the case of Rolls-Royce."

"Hitachi's technological resources were distributed over a wide number of fields, with 90% of the total reached in 14 out of 34 fields. The distinctive competencies in computers, image and sound, and semiconductors accounted for only about 40% of all patenting. Computing increased from 6 to 17% over the period, while electrical devices and equipment declined from 15 to 10%. Nuclear technology remained a niche competence. The 24% of all patenting in the background technologies of instruments and production equipment reflects [Hitachi's] complex supply chain...."

Christensen (1998) argues that "technology diversification, that is, the firm's expansion of its technological asset base" is one of the key driving forces of corporations. To illustrate his points, he presents a case study of Danfoss, a Danish corporation operating within "mechatronical" markets (a fusion of mechanics and electronics). He argues that for Danfoss, "*[t]echnology diversification has been just as significant as product market diversification... Thus, for example the primarily mechanical engineering base of the early Danfoss era has been supplemented by electronics and software capabilities since the 1950s. Capabilities in hydraulics have become a decisive asset in the technology base from the 1960's and onwards. Other more specific technical capabilities (i.e. stainless steel technology, computational fluid dynamics) have been developed in the context of the expanding product portfolio...*" See also Christensen (2002).

Oskarsson (1993) documents the increase in technological diversification in OECD countries at various levels of aggregation (industry, firm, product). He finds a strong positive correlation between sales growth and growth in technology diversification. As case studies, he discusses in detail the technological diversification experienced in telecommunication cables and refrigerators, documenting the various sub-technologies that enter in the production process and their evolution over time. Oskarsson and Sjoberg (1993) provide a similar analysis of mobile telephones. Oskarsson (1993) argues that technological diversification was the result of increased technological opportunities, partly caused by scientific progress and in particular, by rapid technological development in materials technology, physics, electronics, chemistry and computer science. He remarks that the possibility to improve performance and decrease the costs with new technologies not earlier present in the products was the overall reason for the increased technology diversification at the product level.

Gambardella and Torrisi (1998) measured technological diversification of thirty two of the largest U.S. and European electronics firms by calculating the Herfindahl index of each firm's number of patents in 1984–1991. Downstream (product) diversification was also measured by the Herfindahl index using the number of new subsidiaries, acquisitions, joint-ventures and other collaborative agreements reported in trade journals, for the same sectors. Their main findings are that better performance (in terms of sales and profitability) is associated with increased technological diversification and *lower* product diversification. They conclude that technological diversification is the key covariate positively related with various measures of performance.

A number of studies focuses on technological diversification in specific industries. Giuri, Hagedoorn and Mariani (2004) analyze data on 219 firms in Europe, the United States and Japan comprising a broad range of sectors from 1990 to 1997 and argue that technological diversification (defined as before, as an expansion in the set of technologies used by the firm) has been more pronounced than product diversification as a driver of firms' growth. They argued that technological diversification took place both through an in-house expansion of the technology base and through strategic alliances with other firms. Cesaroni et al. (2004) discuss in detail the process of technological diversification of the world-wide largest corporations operating in the chemical processing industry from 1980 to 1996. Mendoca (2004) discusses how the information and communications technologies (ICT) revolution has affected the technological diversification process of different industries. The study finds that ICT has been important in broadening the technology base in many sectors, including Photography and photocopy, Motor Vehicles and Parts, Aerospace, and Machinery. It furthermore finds that its importance is fast rising for Metal and Materials, while not so important for chemicals and related sectors. Prencipe (2001) documents that in the aircraft industry, engine makers maintain a broad range of in-house technological capabilities and that the breadth of these capabilities has increased over time.

Fai (2003) documents that over the period 1930-1990, firms have become more technologically diversified, with the chemical, electrical/electronic and mechanical groups revealing the highest increase in diversification in their technological competencies. She highlights as examples in the chemicals sector the cases of Union Carbide, Standard Oil, Du Pont, and IG Farben, all of which became more diversified over the period 1930-90.

A.3.2 Input diversification

Below, we report evidence that firms can expand by increasing the number of inputs (as opposed to technologies).

Feenstra et al. (1992) provide evidence that input diversification leads to growth and productivity gains. Using data on South Korean conglomerates (chaebols) which are vertically integrated, the authors find that the entry of new input-producing firms into a conglomerate increases the productivity of that conglomerate.

In farming, there are multiple examples of inputs leading to productivity gains and faster growth. For example as, reported by the World Bank: in larger scale crop production, the two short term interventions with the greatest impact are the use (or provision) of high quality seed and of chemical fertilizers (World Bank, 2011, pp. 32). Another more recent example in which the adoption of a new technology can increase productivity, is the case of cell phones. For example, Turkey provided a cell-phone message service to fruit growers warning them of overnight frost risk so they could take protective action to safeguard their fruit buds. The program was a success and increased productivity (World Bank, 2011, pp. 34). Similarly, investment in irrigation systems can mitigate the impact of drought (weather shocks) on crop yields and enhance productivity. World Bank (2011, pp. 33) mentions the development of irrigation systems to enhance agricultural productivity and reduce production volatility. World Bank (2011, pp. 31) notes that the use of fertilizers, modern seeds and agronomic skills could more than double grain output in the Europe and Central Asia and make it less volatile: "For example, fertilizer use in ECA is much below that in Western Europe ... and farm practices are much less sophisticated. These factors translate into highly volatile production and exports from the northern Black Sea Region." (World Bank, 2011, pp. 31)

There is also evidence outside agriculture that firms seek to mitigate the impact of input specific shocks through input substitution. Krysiak (2009) advocates firms using different technologies in the production of a homogeneous good because it reduces the transmission of factor price volatility to product prices. Krysiak (2009) uses the example of electricity generation, where "to a considerable extent" the same firm has different plants that use different technologies requiring different fuel inputs for electricity generation. Similarly, Krysiak (2009) says that large steel-producing firms fit their plants with different energy sources.

Relatedly, Beltramo (1989) remarks that –even within the same plant — manufacturing firms have installed dual-fired equipment such that they have the capability to switch between natural gas and oil at the turn of a valve: "At least partially as a response to curtailments of industrial gas use during the 197Os, many large manufacturing users of natural gas or fuel oil have installed equipment capable of burning either fuel"(Krysiak, 2009, pp. 70). Further, Krysiak's own estimates "indicate a trend away from oil-fired equipment during the period 1974-81, which is sensible in light of the two oil price shocks, among other things, that occurred during this period." This is consistent with the findings for the United States in Blanchard and Gali (cited in paper).

Logistic firms also use different modes of transport to facilitate input substitution (Krysiak, 2009).

A.3.3 Evolution of Input-Output Tables in OECD Countries

This Section illustrates the expansion in the number of input varieties used by different sectors that took place from the late 1960s or early 1970s until 2005 (the exact years depend on data availability). Specifically, we study the evolution over time of the ratio of purchases (direct or indirect) by a given sector from itself relative to total purchases by that sector. If a sector diversifies its input usage, we should see more purchases from other sectors and less from itself.

The data are computed from the OECD input-output tables and are disaggregated into 35 sectors: 1)Agriculture, forestry & fishing; 2) Mining & quarrying; 3) Food, beverages & tobacco; 4) Textiles, apparel & leather; 5) Wood products & furniture; 6) Paper, paper products & printing; 7) Industrial chemicals; 8) Drugs & medicines; 9) Petroleum & coal products; 10) Rubber & plastic products; 11) Non-metallic mineral products; 12) Iron & steel; 13) Non-ferrous metals; 14) Metal products; 15) Non-electrical machinery; 16) Office & computing machinery; 17) Electrical apparatus, nec; 18) Radio, TV & communication equipment; 19) Shipbuilding & repairing; 20) Other transport; 21) Motor vehicles; 22) Aircraft; 23) Professional goods; 24) Other manufacturing; 25) Electricity, gas & water; 26) Construction; 27) Wholesale & retail trade; 28) Restaurants & hotels; 29) Transport & storage; 30) Communication; 31) Finance & insurance; 32) Real estate & business services; 33) Community, social & personal services; 34) Producers of government services; 35) Other producers. Comparable data over time are available for Austria, Canada, Denmark, France, Great Britain, Netherlands, Italy and the United States.[77]

The evolution of the average sectoral share of purchases by a sector from itself are depicted in Figure $A4$ for each of the countries for which we have consistent time-series data. As the plot shows, the average purchases of inputs by a given sector from that same sector (i.e., corresponding to the diagonal elements in an input-output table) have fallen over time for most countries in the sample, as illustrated in the plot below, coinciding with a period in which volatility also went down. Note that the measures are not weighting for the different volatilities (and covariances) intrinsic to the sectors, so it is an imperfect measure of diversification, as argued in Koren and Tenreyro (2007).

Table $A7$ investigates the size and significance of the time elasticities using sector-country-year level data on the share of direct or indirect purchases by a given sector from itself from 1970 to 2007. The table shows the outputs from a regression of the (log) ratio of purchases (direct or indirect) of inputs by a given sector j from itself in country i in year t relative to total purchases from that sector-country in that year on a (log) linear trend. The first column shows the pooled regressions, the second controls for country fixed-effects, and the third controls for country and sector-fixed effects; the latter aims at controlling for

[77] See Berlingieri (2011) for a thorough analysis of the U.S. input-output structure.

heterogeneity across sectors regarding the level usage by different sectors. The results point to a significant trend towards higher usage of inputs from other sectors, consistent with the technological diversification mechanism.

Figure $A4$. Average Ratio of Purchases of Inputs by a Sector from Itself relative to Total Purchases by the Sector

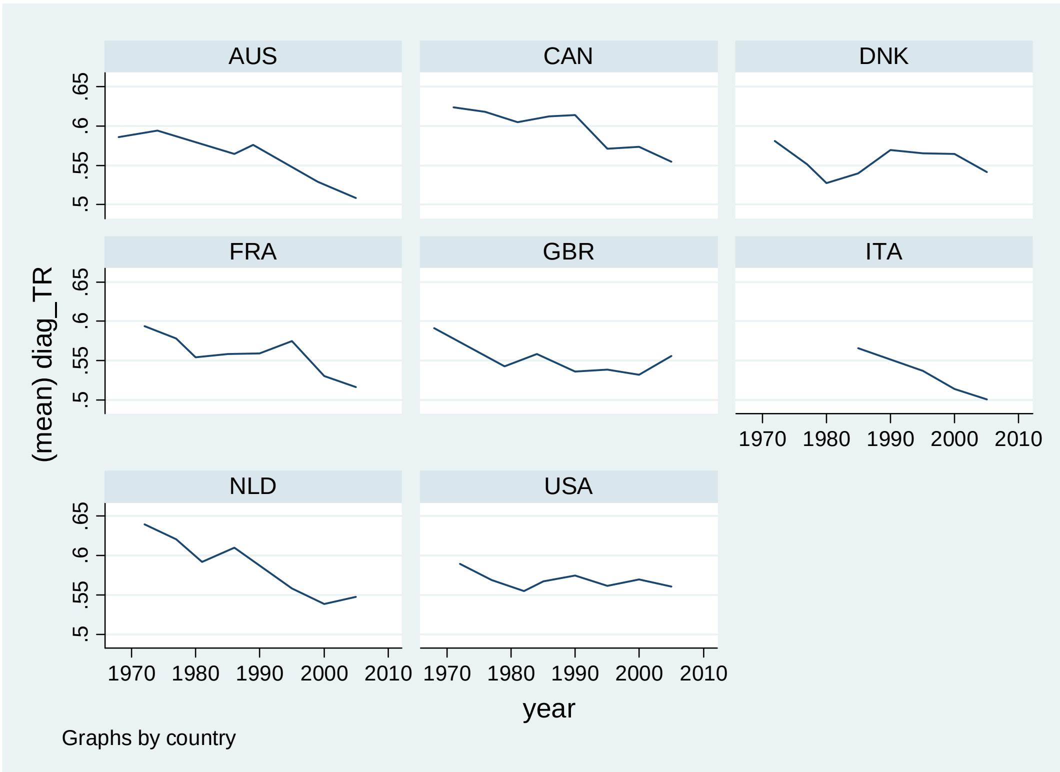


Table $A7$. Trends in Purchases of Inputs by a Sector from Itself relative to Total Purchases by the Sector

Trend	-5.953***	-5.541***	-5.793***
	[0.691]	[0.693]	[0.384]
Country fixed effects	No	Yes	Yes
Industry Fixed Effects	No	No	Yes
Observations	1743	1743	1743
R-squared	0.041	0.072	0.724

Note: Variables are in logs. The dependent variable is direct and indirect purchases of inputs by sector j from itself in country i at time t, relative to total purchases by that sector. The variable is computed using input-output tables from OECD from 1968 to 2005. The panel is unbalanced. Robust standard errors in brackets. *Significant at 10%; **significant at 5%; *** significant at 1%.

A.4 Skewness

For each country, Table A8 reports the skewness in the distribution of annual growth rates. The Table also shows the p-values for the null of normality, based on the sample skewness. In all, about 70 percent of the countries in the sample display negative skewness.

Table *A*8. Skewness in the Distribution of Growth Rates of Real GDP per capita. PWT (PPP adjusted) Data

Country	Skewness (1)	Sample-size adjusted skewness (2)	Skewness test p-values (3)	Number of observations (4)
Albania	-1.595	-1.663	0.000	37
Algeria	-2.709	-2.800	0.000	47
Angola	-1.149	-1.198	0.005	37
Antigua and Barbuda	0.233	0.243	0.511	37
Argentina	-0.339	-0.350	0.297	47
Armenia	-0.654	-0.735	0.207	14
Australia	-1.037	-1.071	0.004	47
Austria	0.115	0.119	0.718	47
Azerbaijan	-0.832	-0.936	0.114	14
Bahamas	-0.904	-0.942	0.020	37
Bahrain	-0.974	-1.016	0.014	36
Bangladesh	-0.945	-0.977	0.008	47
Barbados	-0.439	-0.453	0.181	47
Belarus	-1.871	-2.125	0.002	13
Belgium	-0.354	-0.365	0.277	47
Belize	-0.082	-0.085	0.817	37
Benin	0.813	0.840	0.020	47
Bermuda	-0.907	-0.945	0.019	37
Bhutan	1.564	1.631	0.000	37
Bolivia	-2.482	-2.565	0.000	47
Bosnia and Herzegovina	1.020	1.122	0.045	17
Botswana	0.563	0.582	0.092	47
Brazil	0.077	0.079	0.810	47
Brunei	-0.366	-0.381	0.307	37
Bulgaria	-1.727	-1.801	0.000	37
Burkina Faso	0.777	0.803	0.025	47
Burundi	0.370	0.382	0.256	47
Cambodia	-0.969	-1.011	0.013	37
Cameroon	-0.449	-0.464	0.172	47
Canada	-1.232	-1.273	0.001	47
Cape Verde	0.068	0.070	0.831	47
Central African Republi	-0.295	-0.304	0.362	47
Chad	0.900	0.930	0.011	47
Chile	-2.075	-2.144	0.000	47
China Version 1	-1.627	-1.681	0.000	47
China Version 2	-1.733	-1.790	0.000	47
Colombia	-0.562	-0.581	0.092	47
Comoros	0.382	0.395	0.241	47
Congo, Demna Repna	-0.540	-0.558	0.105	47
Congo, Republic of	0.859	0.888	0.015	47
Costa Rica	-1.633	-1.687	0.000	47
Cote d`Ivoire	0.050	0.052	0.876	47
Croatia	-1.707	-1.877	0.002	17

Table $A8$ continued

Country	Skewness (1)	Sample-size adjusted skewness (2)	Skewness test p-values (3)	Number of observations (4)
Cuba	-0.598	-0.624	0.105	37
Cyprus	-0.895	-0.924	0.011	47
Czech Republic	-2.610	-2.870	0.000	17
Denmark	0.171	0.177	0.594	47
Djibouti	1.083	1.130	0.007	37
Dominica	-1.216	-1.268	0.003	37
Dominican Republic	-0.730	-0.754	0.034	47
Ecuador	0.176	0.182	0.583	47
Egypt	1.102	1.139	0.003	47
El Salvador	-1.125	-1.163	0.002	47
Equatorial Guinea	1.398	1.445	0.000	47
Eritrea	0.608	0.678	0.229	15
Estonia	-1.918	-2.109	0.001	17
Ethiopia	-0.132	-0.137	0.679	47
Fiji	0.444	0.459	0.176	47
Finland	-0.945	-0.977	0.008	47
France	-0.359	-0.370	0.270	47
Gabon	0.240	0.248	0.455	47
Gambia, The	0.269	0.278	0.403	47
Georgia	0.244	0.274	0.629	14
Germany	-0.308	-0.321	0.388	37
Ghana	-0.376	-0.389	0.248	47
Greece	-0.379	-0.392	0.245	47
Grenada	-0.585	-0.610	0.112	37
Guatemala	-0.096	-0.099	0.764	47
Guinea	-0.976	-1.008	0.007	47
Guinea-Bissau	-0.423	-0.437	0.197	47
Guyana	0.291	0.304	0.413	37
Haiti	0.127	0.131	0.691	47
Honduras	-0.318	-0.329	0.326	47
Hong Kong	-0.091	-0.094	0.775	47
Hungary	-1.621	-1.691	0.000	37
Iceland	0.414	0.427	0.206	47
India	-0.245	-0.253	0.447	47
Indonesia	-1.456	-1.505	0.000	47
Iran	-1.898	-1.961	0.000	47
Iraq	-1.801	-1.878	0.000	37
Ireland	-0.143	-0.148	0.655	47
Israel	0.554	0.572	0.097	47
Italy	-0.198	-0.204	0.537	47
Jamaica	0.210	0.217	0.514	47
Japan	0.585	0.604	0.081	47
Jordan	-0.009	-0.009	0.978	47

Table $A8$ continued

Country	Skewness (1)	Sample-size adjusted skewness (2)	Skewness test p-values (3)	Number of observations (4)
Kazakhstan	-0.370	-0.417	0.466	14
Kenya	-0.798	-0.825	0.022	47
Kiribati	-1.668	-1.739	0.000	37
Korea, Republic of	-1.824	-1.885	0.000	47
Kuwait	-0.046	-0.048	0.897	37
Kyrgyzstan	-1.148	-1.291	0.035	14
Laos	0.755	0.787	0.046	37
Latvia	-0.369	-0.415	0.468	14
Lebanon	-1.476	-1.540	0.001	37
Lesotho	-0.002	-0.002	0.994	47
Liberia	-1.274	-1.328	0.002	37
Libya	-0.893	-0.931	0.021	37
Lithuania	-2.187	-2.458	0.000	14
Luxembourg	-0.478	-0.494	0.148	47
Macao	0.988	1.030	0.012	37
Macedonia	-1.178	-1.295	0.023	17
Madagascar	0.369	0.381	0.257	47
Malawi	0.048	0.049	0.881	47
Malaysia	0.467	0.482	0.157	47
Maldives	-0.064	-0.067	0.856	37
Mali	-0.984	-1.017	0.006	47
Malta	0.653	0.681	0.079	37
Marshall Islands	1.027	1.071	0.010	37
Mauritania	2.207	2.280	0.000	47
Mauritius	-0.192	-0.199	0.549	47
Mexico	-1.118	-1.155	0.002	47
Micronesia, Fed. Sts.	1.551	1.617	0.000	37
Moldova	-1.602	-1.786	0.005	15
Mongolia	-1.883	-1.963	0.000	37
Montenegro	-1.539	-1.692	0.005	17
Morocco	0.734	0.758	0.033	47
Mozambique	-0.374	-0.386	0.251	47
Namibia	0.363	0.375	0.264	47
Nepal	-0.737	-0.761	0.032	47
Netherlands	-0.235	-0.242	0.466	47
New Zealand	-0.613	-0.633	0.069	47
Nicaragua	-1.873	-1.936	0.000	47
Niger	-1.721	-1.778	0.000	47
Nigeria	0.196	0.203	0.540	47
Norway	-0.118	-0.122	0.711	47
Oman	-0.178	-0.186	0.614	37
Pakistan	0.782	0.808	0.024	47
Palau	-1.347	-1.405	0.001	37

Table $A8$ continued

Country	Skewness (1)	Sample-size adjusted skewness (2)	Skewness test p-values (3)	Number of observations (4)
Panama	0.090	0.093	0.779	47
Papua New Guinea	3.529	3.646	0.000	47
Paraguay	0.663	0.685	0.051	47
Peru	-1.592	-1.645	0.000	47
Philippines	-0.447	-0.462	0.174	47
Poland	-1.905	-1.986	0.000	37
Portugal	-1.226	-1.267	0.001	47
Puerto Rico	-0.304	-0.315	0.347	47
Qatar	0.382	0.399	0.287	37
Romania	-0.641	-0.663	0.058	47
Russia	-1.110	-1.220	0.031	17
Rwanda	-0.189	-0.195	0.555	47
Samoa	-0.260	-0.271	0.463	37
Sao Tome and Principe	-0.342	-0.356	0.339	37
Saudi Arabia	1.216	1.268	0.003	37
Senegal	-0.056	-0.058	0.860	47
Seychelles	-0.672	-0.694	0.048	47
Sierra Leone	-0.645	-0.667	0.059	46
Singapore	-1.168	-1.207	0.002	47
Slovak Republic	-2.337	-2.531	0.000	20
Slovenia	-2.158	-2.372	0.000	17
Solomon Islands	-0.264	-0.275	0.458	37
Somalia	-0.876	-0.913	0.023	37
South Africa	-0.285	-0.295	0.377	47
Spain	0.481	0.497	0.146	47
Sri Lanka	-0.116	-0.119	0.717	47
St. Kitts & Nevis	-0.830	-0.865	0.030	37
St. Lucia	0.482	0.503	0.184	37
St.Vincent & Grenadin	-0.330	-0.344	0.356	37
Sudan	-0.812	-0.847	0.033	37
Suriname	-1.096	-1.143	0.006	37
Swaziland	1.101	1.149	0.006	37
Sweden	-0.936	-0.967	0.009	47
Switzerland	-1.687	-1.744	0.000	47
Syria	0.250	0.258	0.438	47
Taiwan	-0.252	-0.260	0.435	47
Tajikistan	-1.170	-1.315	0.032	14
Tanzania	0.373	0.385	0.253	47
Thailand	-1.609	-1.663	0.000	47
Togo	-0.375	-0.388	0.250	47
Tonga	2.016	2.103	0.000	37
Trinidad &Tobago	-0.256	-0.264	0.428	47
Tunisia	0.549	0.568	0.102	46

Table $A8$ continued

Country	Skewness (1)	Sample-size adjusted skewness (2)	Skewness test p-values (3)	Number of observations (4)
Turkey	-1.225	-1.265	0.001	47
Turkmenistan	-0.842	-0.947	0.110	14
Uganda	-1.159	-1.197	0.002	47
Ukraine	-1.095	-1.231	0.043	14
United Arab Emirates	3.049	3.180	0.000	37
United Kingdom	-0.371	-0.383	0.255	47
United States	-0.517	-0.534	0.119	47
Uruguay	-0.876	-0.905	0.013	47
Uzbekistan	-0.976	-1.073	0.054	17
Vanuatu	0.740	0.772	0.050	37
Venezuela	-0.389	-0.402	0.233	47
Vietnam	-0.611	-0.637	0.098	37
Yemen	1.461	1.597	0.006	18
Zambia	2.192	2.265	0.000	47
Zimbabwe	-0.891	-0.920	0.012	47

Note: PPP adjusted unbalanced panel data, 1960-2007, as available from PWT. (1) Skewness is measured as m3/m2^(3/2), where m3 and m2 are respectively the sample third and second central moments of the growth rate, computed over the available period. (2) Measures the size-adjusted skewness of the distribution, given the number of observations in (4); the factor of adjustment is sqr[n(n-1)]/(n-2). (3) Reports the p-values for a test of the null of symmetry under normality (D'Agostino test). (4) Number of observations.

A.5 Sample

Table $A9$ shows the list of countries included in the baseline regressions using PWT version 6.3 data. Table $A10$ shows the subsample of countries with data on GDP per capita in 1870 from Maddison (2010). In computing volatility over a decade for the various figures and regressions, we only consider countries with five or more years of data over a decade, both in PWT and WDI.

Table $A9$. List of countries from Penn World Tables.

Albania	Djibouti	Lebanon	Samoa
Algeria	Dominica	Lesotho	Sao Tome and Principe
Angola	Dominican Republic	Liberia	Saudi Arabia
Antigua and Barbuda	Ecuador	Libya	Senegal
Argentina	Egypt	Lithuania	Seychelles
Armenia	El Salvador	Luxembourg	Sierra Leone
Australia	Equatorial Guinea	Macao	Singapore
Austria	Eritrea	Macedonia	Slovak Republic
Azerbaijan	Estonia	Madagascar	Slovenia
Bahamas	Ethiopia	Malawi	Solomon Islands
Bahrain	Fiji	Malaysia	Somalia
Bangladesh	Finland	Maldives	South Africa
Barbados	France	Mali	Spain
Belarus	Gabon	Malta	Sri Lanka
Belgium	Gambia, The	Marshall Islan	St. Kitts & Nevis
Belize	Georgia	Mauritania	St. Lucia
Benin	Germany	Mauritius	St.Vincent & Grenadines
Bermuda	Ghana	Mexico	Sudan
Bhutan	Greece	Micronesia, Fe	Suriname
Bolivia	Grenada	Moldova	Swaziland
Bosnia and Herzegovina	Guatemala	Mongolia	Sweden
Botswana	Guinea	Montenegro	Switzerland
Brazil	Guinea-Bissau	Morocco	Syria
Brunei	Guyana	Mozambique	Taiwan
Bulgaria	Haiti	Namibia	Tajikistan
Burkina Faso	Honduras	Nepal	Tanzania
Burundi	Hong Kong	Netherlands	Thailand
Cambodia	Hungary	New Zealand	Togo
Cameroon	Iceland	Nicaragua	Tonga
Canada	India	Niger	Trinidad &Tobago
Cape Verde	Indonesia	Nigeria	Tunisia
Central African Republic	Iran	Norway	Turkey
Chad	Iraq	Oman	Turkmenistan
Chile	Ireland	Pakistan	Uganda
China Version 1	Israel	Palau	Ukraine
China Version 2	Italy	Panama	United Arab Emirates
Colombia	Jamaica	Papua New Gu	United Kingdom
Comoros	Japan	Paraguay	United States
Congo, Demna Repna	Jordan	Peru	Uruguay
Congo, Republic of	Kazakhstan	Philippines	Uzbekistan
Costa Rica	Kenya	Poland	Vanuatu
Cote d`Ivoire	Kiribati	Portugal	Venezuela
Croatia	Korea, Republic of	Puerto Rico	Vietnam
Cuba	Kuwait	Qatar	Yemen
Cyprus	Kyrgyzstan	Romania	Zambia
Czech Republic	Laos	Russia	Zimbabwe
Denmark	Latvia	Rwanda	

Table $A10$. List of countries in Maddison's subsample

Albania	Hungary	Portugal
Algeria	India	Romania
Argentina	Indonesia	South Korea
Australia	Iran	Singapore
Austria	Iraq	South Africa
Belgium	Ireland	Spain
Brazil	Italy	Sri Lanka
Bulgaria	Jamaica	Sweden
Burma	Japan	Switzerland
Canada	Jordan	Syria
Chile	Lebanon	Taiwan
China	Malaysia	Thailand
Czechoslovakia	Mexico	Tunisia
Denmark	Morocco	Turkey
Egypt	New Zealand	United Kingdom
F. USSR	Nepal	Uruguay
Finland	Netherlands	United States
France	North Korea	Venezuela
Germany	Norway	Vietnam
Ghana	Philippines	W. Bank & Gaza
Greece	Poland	Yugoslavia
Hong Kong		

A.6 An Empirical Illustration

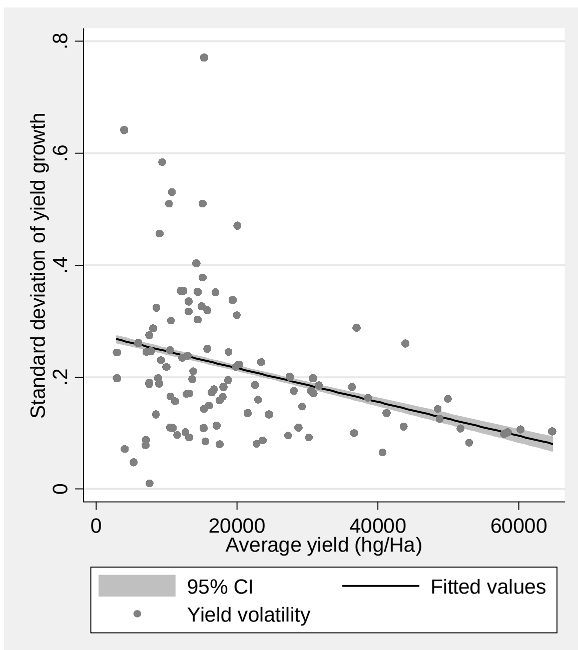
Consider, as a specific illustration, the following example from agriculture.[78] Growing wheat with only land and labour as inputs renders the yield vulnerable to various idiosyncratic shocks. In contrast, using land and labour together with artificial irrigation, different varieties of fertilizers, pesticides, etc., can make wheat-growing not only more productive on average but also less risky, because farmers have more options to substitute failing, unavailable, or simply temporarily expensive inputs (e.g., a temporary drought can be tackled with irrigation). Figure $A5$ depicts the volatility of wheat yield (calculated as the standard deviation of annual yield changes) of 106 wheat producers against the average wheat yield of the country between 1961 and 2003. The measure of yield is strictly technological: harvested production per unit of harvested land area. As the plot shows, yield volatility declines sharply with the average yield.[79] This remains true if we control for differences in climate across countries, including the volatility of rainfall and temperature (which are the most likely sources of shocks to land productivity). The biggest culprit for a negative

[78] It is of relevance to draw examples from agriculture because it is a prominent sector in many developing countries; focusing on a narrowly defined sector allows us to illustrate that the technological-diversification mechanism operates not only across sectors, but also *within* sectors.

[79] Data source: Food and Agriculture Organization of the United Nations, FAOSTAT Yearbook 2005.

(and strictly technological) relation between volatility and average yield at such finely disaggregated level is the availability and use of agricultural inputs, which vary substantially with development.[80] For example, of the top 20 wheat producers, India uses 2.3 tractors per 1,000 acres of arable land; this number is 128.8 for Germany. Fertilizer use also varies hugely. India uses 21.9 tons of nitrogenous fertilizers per 1,000 acres; Germany uses 183.8 tons.[81] To the extent that input diversification is intrinsically related to capital deepening, the technological diversification channel we emphasize also implies that capital deepening leads to both higher average yields and lower volatility. A similarly negative relation appears when we plot wheat yield volatility against the level of development of the country (results available from the authors).

Figure $A5$. Wheat Yield Volatility and Average Wheat Yield



Note: The Figure plots the volatility of wheat yield (standard deviation of annual yield changes) against (log) average wheat yield for 106 countries. OLS regression line and 95% confidence intervals also shown. Source: FAOSTAT 2005.

The model we present will more formally illustrate how (endogenously generated) differences across countries and over time in the use of inputs can affect volatility and its relation with the level of development.

[80] Recall the results hold after controlling for the most likely shocks.
[81] As before, the data come from FAOSTAT Yearbook 2005.

B Proofs

B.1 Proof of Proposition 1

Constructing the equilibrium. We prove existence by constructing the equilibrium.

First, observe that because the externality affects the productivity of labor, we can think of the economy as having $A(\mathcal{M})L$ units of effective labor. We let $\omega(\mathcal{M}) = w(\mathcal{M})/A(\mathcal{M})$ denote the wages of effective labor.

We first characterize the static decisions of firms and the static equilibrium (i.e., market clearing) for a given amount of aggregate externality. We then proceed to show how the entry of new firms makes the aggregate returns to scale constant, which makes aggregate output, wages, profits etc., linear in the total number of varieties N, as stated in the proposition.

Using the first-order condition for optimal pricing (13), we can express a firm's operating profits as

$$\pi(n, \mathcal{M}) = \frac{(\varepsilon - 1)^{\varepsilon-1}}{\varepsilon^{\varepsilon}} Y(\mathcal{M})\omega(\mathcal{M})^{1-\varepsilon} n.$$

Profits are linear in n. They also increase in aggregate demand, and decrease in effective wages.

Combining equations (4), (5), and (13), labor demand by firm n is

$$l(n, \mathcal{M}) = Y(\mathcal{M})\omega(\mathcal{M})^{-\varepsilon} \left(\frac{\varepsilon}{\varepsilon - 1}\right)^{-\varepsilon} n. \tag{A1}$$

Labor market clearing implies

$$A(\mathcal{M})L = \int_n A(\mathcal{M})l(n, \mathcal{M})\mathrm{d}\mathcal{M} = Y(\mathcal{M})\omega(\mathcal{M})^{-\varepsilon} \left(\frac{\varepsilon}{\varepsilon - 1}\right)^{-\varepsilon} \int_n n\mathrm{d}\mathcal{M} \tag{A2}$$

or, with the N notation

$$L = \frac{Y(\mathcal{M})}{A(\mathcal{M})}\omega(\mathcal{M})^{-\varepsilon} \left(\frac{\varepsilon}{\varepsilon - 1}\right)^{-\varepsilon} N.$$

where

$$Y(\mathcal{M}) = \left[\int_0^1 y(j)^{(\varepsilon-1)/\varepsilon}\,\mathrm{d}j\right]^{\varepsilon/(\varepsilon-1)} = \left[\int y(n, \mathcal{M})^{(\varepsilon-1)/\varepsilon}\mathrm{d}\mathcal{M}\right]^{\varepsilon/(\varepsilon-1)} \tag{A3}$$

is the aggregator function.

Using the equations for individual labor demand (A1), the production function (4), and the aggregator function (A3), we can write the aggregate supply of the final good as

$$\begin{aligned} Y(\mathcal{M}) &= Y(\mathcal{M})\omega(\mathcal{M})^{-\varepsilon} \left(\frac{\varepsilon}{\varepsilon - 1}\right)^{-\varepsilon} \left[\int n\mathrm{d}\mathcal{M}\right]^{\varepsilon/(\varepsilon-1)} \\ &= Y(\mathcal{M})\omega(\mathcal{M})^{-\varepsilon} \left(\frac{\varepsilon}{\varepsilon - 1}\right)^{-\varepsilon} N^{\varepsilon/(\varepsilon-1)}, \end{aligned}$$

which allows us to express real wages as

$$w(\mathcal{M}) = A(\mathcal{M})\omega(\mathcal{M}) = \frac{\varepsilon - 1}{\varepsilon} N^{1/(\varepsilon-1)} A(\mathcal{M}). \tag{A4}$$

This gives equation (22).

Substituting this into labor market clearing (A2),

$$Y(\mathcal{M}) = A(\mathcal{M}) L N^{1/(\varepsilon-1)}. \tag{A5}$$

This gives equation (23).

Substituting wages into the first-order condition of pricing (13) yields the equilibrium pricing equation (24).

Substituting in (A4) and (A5) into the profit function (6),

$$\pi(n, \mathcal{M}) = \frac{1}{\varepsilon} A(\mathcal{M}) L N^{(2-\varepsilon)/(\varepsilon-1)} n.$$

Let

$$\bar{\pi} \equiv \frac{\pi(n, \mathcal{M})}{nL} = \frac{1}{\varepsilon} A(\mathcal{M}) N^{(2-\varepsilon)/(\varepsilon-1)}$$

denote profits per variety per capita. Profits increase in the strength of the externality, in country size, and depend on the overall number of varieties as follows. If $\varepsilon < 2$, then the demand externality coming from love of varieties is stronger than the competitive effect of more varieties, and profits increase in N. If $\varepsilon > 2$, then the competitive effect is stronger and profits decrease in N. As we show below, firm entry will stabilize profits at a constant value by changing the external effect $A(\mathcal{M})$. By assumption 17, the external effect decrease in the number of new entrants, so profits also decrease in the number of new firms.

We have completely characterized all static decisions.

Free entry and external effects. For new entrants, we can write the Bellman equation A13 as

$$\rho V(0, \mathcal{M}) = -\kappa L + \eta [V(1, \mathcal{M}) - V(0, \mathcal{M})].$$

Entrants do not have productive varieties, so their value is composed of the flow costs of adoption κL and the potential capital gains coming from successfully acquiring the first variety, $V(1, \mathcal{M}) - V(0, \mathcal{M})$, which happens with arrival rate η. Free entry ensures $V(0, \mathcal{M}) = 0$, which, together with the Bellman equation pins down

$$V(1, \mathcal{M}) \equiv v = \kappa L / \eta.$$

The value of size-1 firms is constant, independent of the state of the economy. Since for $n = 0, 1$ we have $V(n, \mathcal{M}) = vn$, we guess that the value function is also linear in the remainder of its domain. We can then write the the first-order condition for optimal adoption as

$$g'(\lambda) L = v$$

and the Bellman equation as

$$\rho v = \pi(\mathcal{M}) - g(\lambda) + \lambda v - \gamma v.$$

We have made use of the linearity of V in n and its independence of $\mathcal{M}$ to cancel the terms depending on $\mathcal{M}$ and then dividing through by n.

Clearly, this Bellman equation holds for all $\mathcal{M}$ if and only if $\pi(\mathcal{M})$ is constant at

$$\bar{\pi} = g(\lambda) + (\rho + \gamma - \lambda)v.$$

Per capita profits per variety have to compensate for the cost of adoption and the opportunity cost of firm value, which, in turn depends on the discount rate ρ and on the expected rate of firm growth $\lambda - \gamma$.

Using the formula for per-variety profits, the equilibrium condition ensuring free entry can be written as

$$A(m_0, N) = \varepsilon \bar{\pi} N^{(\varepsilon-2)/(\varepsilon-1)}. \tag{A6}$$

Given that $A(m_0, N)$ is monotonic in m_0, this condition uniquely pins down the number of new firms for any given N. Substituting in the formulas for wages and output, we get

$$\begin{aligned} w(\mathcal{M}) &= (\varepsilon - 1)\bar{\pi} N, \\ Y(\mathcal{M}) &= \varepsilon \bar{\pi} N L, \end{aligned}$$

as claimed in the proposition.

Aggregate dynamics. Given the optimal adoption intensity by incumbents, λ, and the mass of new entrants m_0, we now turn to characterizing aggregate dynamics.

Recall that $m_i(t)$ is the measure of firms using exactly i varieties at time t. A certain fraction of firms of size $i-1$ are successful in adopting variety i in every instant. Similarly, a certain fraction of firms of size i are successful in adopting variety $i+1$ in every instant. As long as none of the varieties fail,

$$\mathrm{d}m_i(t) = [\mu(i-1)m_{i-1}(t) - \mu(i)m_i(t)]\,\mathrm{d}t,$$

where $\mu(i) = \lambda i$ for $i > 0$ and $\mu(i) = \eta$ for $i = 0$. A $\mu(i-1)m_{i-1}(t)$ measure of firms are going to be successful in adopting variety i, so they will become size i. A $\mu(i)m_i(t)$ measure of size-i firms are going to be successful in adopting variety $i+1$, so they will no longer be size i.

If variety k fails, which happens with arrival rate γ, each firm using this variety will have its size reduced by one. That is, they will add to the mass of firms one below their current size. Letting $\mathrm{d}J_k(\gamma t)$ denote the failure of variety k, the jumps in m_i are

$$\mathrm{d}m_i(t) = m_{i+1}(t) \sum_{k=1}^{i+1} \mathrm{d}J_k(\gamma t) - m_i(t) \sum_{k=1}^{i} \mathrm{d}J_k(\gamma t).$$

If any of the first $i+1$ variety fails, the size-$i+1$ firms will become size i, and add to the mass of m_i. If any of the first i variety fails, then size-i firms also move down by one, and reduce m_i.

Taking the deterministic and the jump part together,

$$\mathrm{d}m_i = [\mu(i-1)m_{i-1}(t) - \mu(i)m_i(t)]\,\mathrm{d}t + m_{i+1}\sum_{k=1}^{i+1}\mathrm{d}J_k(\gamma t) - m_i\sum_{k=1}^{i}\mathrm{d}J_k(\gamma t).$$

Indeed this law of motion is the same as (8) with F and G properly defined, and writing out $\mu(i)$,

$$F_i(\mathcal{M}) = \begin{cases} \lambda(i-1)m_{i-1} - \lambda i m_i & \text{if } i > 1, \\ \eta m_0 - \lambda m_1 & \text{if } i = 1. \end{cases}$$

$$G_{ik}(\mathcal{M}) = \begin{cases} m_{i+1} - m_i & \text{if } k \le i, \\ m_{i+1} & \text{if } k = i+1, \\ 0 & \text{if } k > i+1. \end{cases}$$

for all $i > 0$ and k. For $i = 0$, the free entry condition A6 gives the mass of firms.

B.2 Lemma 1

Lemma 1. Let $J(\alpha t)$ denote a Poisson process with arrival rate α. The expected change in J and the variance of the change are $\mathrm{E}\,\mathrm{d}J(\alpha t) = \mathrm{Var}\,\mathrm{d}J(\alpha t) = \alpha\mathrm{d}t$,

Proof Over a $\mathrm{d}t$ period of time, the change in a Poisson process is a random integer with a Poisson distribution with parameter $\alpha\mathrm{d}t$. The mean and variance of the Poisson distribution is equal to $\alpha\mathrm{d}t$.

B.3 Proof of Proposition 2

The proof follows directly by applying Lemma 1 to equation (10). $\mathrm{E}(\mathrm{d}n) = [\lambda - \gamma]n\mathrm{d}t$, and we divide by n to obtain the result. $\mathrm{Var}(\mathrm{d}n) = [\lambda + \gamma]n\mathrm{d}t$, and we divide by n^2 to obtain the result.

B.4 Proof of Proposition 3

The proof follows directly by applying Lemma 1 to equation (30). $\mathrm{E}(\mathrm{d}N) = [\lambda N + \eta m_0 - \gamma N]\mathrm{d}t$, and we divide by N to obtain the result. $\mathrm{Var}(\mathrm{d}N) = \gamma\sum_{k=1}^{\infty} M_k^2\mathrm{d}t$, and we divide by N^2 to obtain the result.

B.5 Proof of Proposition 4

Proposition 3 gives the expected growth rate of output as

$$\lambda + \eta\frac{m_0}{N} - \gamma.$$

By Proposition 1, wages are also linear in N, so this is also the expected growth rate of wages. Because Proposition 1 has already shown that λ is a constant determined by κ/η, it only remains to be shown that $\frac{m_0}{N}$ converges to zero as N grows without bound. In that case, investment converges to $I = g(\lambda)LN$, so it will also grow at the same constant rate. Because output is consumption plus investment, the growth rate of consumption is the same.

The measure of new firms m_0 is given as the solution to the free entry condition A6. Log differentiating that equation with respect to m_0 and N,

$$\theta_{m_0}(\mathcal{M})\mathrm{d}\ln m_0 + \theta_N(\mathcal{M})\mathrm{d}\ln N = \left(1 - \frac{1}{\varepsilon - 1}\right)\mathrm{d}\ln N,$$

where θ_{m_0} is the elasticity of $A(m_0, N)$ with respect to m_0, holding N fixed, and θ_N is defined correspondingly as the elasticity with respect to N holding m_0 fixed. Given the assumption about $\theta_{m_0}(\mathcal{M})$ and $\theta_N(\mathcal{M})$, the mass of new firms m_0 is either decreasing in N, or increasing, but at a rate less than one,

$$\frac{\mathrm{d}\ln m_0}{\mathrm{d}\ln N} = \frac{1 - 1/(\varepsilon - 1) - \theta_N(\mathcal{M})}{\theta_{m_0}(\mathcal{M})} < 1.$$

Intuitively, as more varieties increase the profits available in the economy (if $1/(\varepsilon - 1) + \theta_N > 1$), more new firms will want to enter. However, their entry pushes down profits fast enough so that the mass of new firms cannot increase as fast as N. This implies that the ratio m_0/N converges to zero, as required.

B.6 Proof of Proposition 5

Consider what happens when an infinitesimal number of firms Δ adopts a variety k. (We denote by ($'$) the new values.) As these firms have added one more variety, the overall number of varieties goes up by Δ:

$$N' = N + \Delta.$$

That is, $\lim_{\Delta \to 0} \frac{N' - N}{\Delta} = 1 > 0$. Hence, output always increases. Before the adoption of variety k, its contribution to output was $s_k \geq 0$. After adoption, the contribution of the various technologies become

$$\begin{aligned} s'_k &= (N s_k + \Delta)/N' \\ s'_i &= N s_i / N' \text{ for all } i \neq k, \end{aligned}$$

and the new variance is given by:

$$\mathrm{Var}' = \left(\frac{N}{N'}\right)^2 \left(\sum\nolimits_{i=1}^{\infty} s_i^2 + (\Delta/N)^2 + 2 s_k \Delta/N\right).$$

The change in variance is hence $\mathrm{Var}' - \mathrm{Var} = \left(\frac{N}{N+\Delta}\right)^2 \left(\sum_{i=1}^{\infty} s_i^2 + (\Delta/N)^2 + 2 s_k \Delta/N\right) - \sum_{i=1}^{\infty} s_i^2$, or, in terms of derivatives:

$$\lim_{\Delta \to 0} \frac{\mathrm{Var}' - \mathrm{Var}}{\Delta} = -\frac{2}{N}\left(\sum\nolimits_{i=1}^{\infty} s_i^2 - s_k\right),$$

which is negative if and only if $\sum_{i=1}^{\infty} s_i^2 > s_k$.[82] Hence, as long as $\sum_{i=1}^{\infty} s_i^2 > s_k$, volatility decreases with the adoption of variety k.[83] Because $\lim_{i\to\infty} s_i = 0$, there is always an index K (a frontier variety) above which all varieties are rare enough to satisfy this condition. Adopting frontier varieties hence always leads to lower volatility. The individual firms adopting technology k always become less volatile, even if aggregate volatility increases (that is, even if the share of that variety in the economy s_k is already big).

B.7 Proof of Proposition 6

Consider the consequences of a negative shock that destroys variety k. The number of firms using this variety is $\sum_{i=k}^{\infty} m_i = N s_k$ (by definition of s_k). The overall number of varieties falls to $N' = (1 - s_k)N$ and output correspondingly falls to $Y' = (1 - s_k)Y$. The new shares in the economy are given by:

$$s_i' = s_i/(1 - s_k) \text{ for all } i < k,$$
$$s_i' = s_{i+1}/(1 - s_k) \text{ for all } k \leq i$$

and the new variance is given by:

$$\text{Var}' = \frac{1}{(1 - s_k)^2} \left(\sum_{i=1}^{\infty} s_i^2 - s_k^2 \right).$$

The change in variance is hence:

$$\begin{aligned} \text{Var}' - \text{Var} &= \left[\frac{1}{(1 - s_k)^2} - 1 \right] \sum_{i=1}^{\infty} s_i^2 - \frac{s_k^2}{(1 - s_k)^2} \\ &= \frac{s_k}{(1 - s_k)^2} \left[(2 - s_k) \sum_{i=1}^{\infty} s_i^2 - s_k \right], \end{aligned}$$

which is positive if an only if $\sum_{i=1}^{\infty} s_i^2 > \frac{s_k}{2 - s_k}$. In words, as long as s_k is not too big, expected volatility increases with the destruction of variety k. This happens together with the unambiguous decline in output caused by the destruction of that variety. Volatility might decrease only if the production process relies strongly on variety k. In that case, the disappearance of that variety leads to higher diversification for the economy. Again, there always exists a frontier variety K such that the destruction of all varieties $k > K$ lead to an increase in volatility and a decline in income.

Note that because $s_k > \frac{s_k}{2 - s_k}$, the destruction of a variety is less likely to induce a positive correlation between volatility and development than the adoption of existing varieties.

[82] The limit results from l'Hôpital's rule.

[83] As an example, consider the following numerical illustration. The distribution of the number of firms with exactly i varieties (m_i) is given by $\{m_1, m_2, m_3, m_4\} = \{\frac{1}{10}, \frac{1}{10}, \frac{4}{10}, \frac{4}{10}\}$; the overall number of varieties in the economy is then $N = \sum_{i=k}^{4} i m_i = 3.1$ and the shares of each variety in the economy are $\{s_1; s_2; s_3; s_4\} = \{0.32; 0.29; 0.26; 0.13\}$, with $\sum_{k=1}^{4} s_k^2 = 0.272$ (and $Var = 0.272\gamma$). Hence $\sum_{k=1}^{4} s_k^2 < s_2$. Adoption of variety 2 by firms with only variety 1 can hence lead to an increase in output and an increase in volatility. Indeed, if all m_1 firms adopt variety 2, we have: $\{m_1', m_2', m_3', m_4'\} = \{0, \frac{2}{10}, \frac{4}{10}, \frac{4}{10}\}$, which implies $N' = 3.2$ and $\{s_1'; s_2'; s_3'; s_4'\} = \{0.31; 0.31; 0.25; 0.13\}$, leading to $Var' = \gamma \sum_{k=1}^{4} s_k^2 = 0.273\gamma > Var$. Because variety 2 was already widely used, increasing its usage by firms of size 1 made the economy more exposed to shocks to that variety.

B.8 Proof of Proposition 7

We will show that in an economy where the overall number of varieties is N, volatility is bounded from above by γ/N. Since GDP is linear in N, the statement in the proposition follows immediately.

Take an economy with a given average variety usage, N. To simplify notation, define $M_k = \sum_{i=k}^{\infty} m_i$. Volatility equals $\gamma \sum_{k=1}^{\infty} s_k^2$, where $s_k = M_k/N$ is the share of variety k in overall GDP. Each variety k is used by at most a unit measure of firms, $M_k \leq 1$. What is the highest possible volatility in this economy conditional on its level of GDP per capita, N? Note that this exercise differs from the one discussed on page 26, where we looked at the unconditional minimum and maximum of volatility, also changing average GDP at the same time.

We need to find the technology distribution $\{s_k\}$ that maximizes:

$$\max_{\{s_k\}} \gamma \sum_{k=1}^{\infty} s_k^2$$

$$\text{s.t. } 0 \leq M_k \leq 1$$

$$\sum_{k=1}^{\infty} M_k = N,$$

with $s_k = M_k/N$. The maximum is attained when the first N varieties are used by all firms, $M_k = 1$ for $k = 1, ..., N$ and no other varieties are used by any firms, $M_k = 0$ for all $k > N$. The maximum volatility is $\gamma \sum_{k=1}^{N} (1/N)^2 = \gamma/N$.

It may seem counterintuitive at first that an even distribution of varieties maximizes volatility. However, this is not an even distribution of all possible varieties, as those with index higher than N are not used at all. This is in fact the most concentrated distribution that is consistent with an average variety use of N.

C Robustness of Numerical Results

Section III reported numerical results for the calibrated model and showed how these results depended on the arrival rate of technology shocks, γ. In this Section we demonstrate that the parameters governing the entry of new firms, η, the strength of the externalities θ_N and θ_{m_0}, and the elasticity of substitution ε have no significant effect on the quantitative results.

Table $A11$ reports, for various alternative parameter values, the regression coefficients of log volatility on log GDP per capita (both in the cross section and in the time series) using the model generated data, and the simulated dispersion of log GDP per capita in 1960. These are the same statistics that are reported in Table 3. We report the mean and standard deviation of the statistics across 100 simulations.

Table $A11$. Volatility and Development under Alternative Parametrizations

	Elasticity of Substitution, ε			Success Rate of New Entrants, η				Stronger Externalities
	2.1	3	5	0.05	0.1	0.15	0.2	
Cross-sectional slope (and std. dev.) of volatility on development	-0.265 (0.034)	-0.266 (0.045)	-0.267 (0.033)	-0.265 (0.036)	-0.268 (0.031)	-0.263 (0.035)	-0.264 (0.031)	-0.263 (0.033)
Time-series slope (and std. dev.) of volatility on development	-0.459 (0.052)	-0.458 (0.055)	-0.451 (0.056)	-0.444 (0.050)	-0.448 (0.060)	-0.445 (0.056)	-0.454 (0.061)	-0.460 (0.055)
Standard deviation of log-GDP per capita in 1960	0.725 (0.061)	0.729 (0.071)	0.720 (0.047)	0.728 (0.056)	0.725 (0.046)	0.729 (0.056)	0.726 (0.055)	0.730 (0.048)

The table shows, correspondingly, the cross-sectional and within-country slope coefficients and standard deviations (in parentheses) from regressions of (log) volatility of annualized quarterly growth rates computed over non-overlapping decades on the average (log) level of development in the decade; a constant (not reported) is included in each regression. The different columns represent different alternative parameter settings in the simulation. All other parameters are set at their baseline value, except in the last column, where, to satisfy sufficient condition (17), we set ε=1.6, θN=0 and θm0=1. Also see notes to Table 3 in main text.

Columns 1 through 3 report simulation results with different elasticities of substitution across varieties, ε. In all specification we set $\gamma = 0.1$, and all other parameters are held at their baseline values. In these simulations, we only consider values of $\varepsilon > 2$, but the last column of the table entertains $\varepsilon = 1.6 < 2$. As ε varies between 2.1 and 5, the simulated statistics are virtually identical, and all are within one standard deviation of the other. The intuition is as follows. A higher epsilon reduces the aggregate demand externality, because varieties are better substitutes and new varieties do not create as much demand for other varieties. This means that profits per variety decrease fast as N increases. At the same time, new firms will respond to this profit reduction by exiting (or entering at a slower rate). This will counteract the demand externality, and will increase the profits per variety, resulting in a constant growth rate.

Columns 4 through 7 report results for different success rate of entrants, η. As said, this rate may matter because faster entry of new firm increases the expected growth rate, as well as the prevalence of small firms in the economy. In practice, the contribution of entrants to aggregate dynamics is small and vanishes over time, so the results are almost identical. The intuition for this is straightforward. Proposition 4 shows that the effect of new firms on aggregate dynamics vanishes in the long run. The contribution of new firms to growth rates is already very small by the time the process reaches the sample period 1960-2008 and hence new firms (and the parameters governing their entry) have a fairly small impact on aggregate volatility.

In the last column of the table, we report the results from a simulation in which several parameters are allowed to vary. In particular, we set $\varepsilon = 1.6$, $\theta_N = 0$, and $\theta_{m_0} = 1$. We choose $\varepsilon < 2$ to highlight that our results do not depend on particularly high elasticities of substitution. When $\varepsilon < 2$, however, we have to make congestion externalities stronger to satisfy the sufficient condition for balanced-expected growth (17). Again, the results are almost identical to the baseline results.

Finally, Table $A12$ reports the results when there are no external effects, $\theta_N = \theta_{m_0} = 0$ and $\varepsilon = 2$, for different values of γ. When there are no external effects, $\varepsilon = 2$ is needed to ensure the existence of an expected balanced growth path. As the table illustrates, the relationship between volatility and development is not significantly altered by this modification vis-à-vis the baseline relationship.

Table $A12$. Volatility and Development: Results for Different γ.
No external effects $\theta_N = \theta_{m_0} = 0$ and $\varepsilon = 2$

	Poisson Parameter γ			
	0.05	0.10	0.15	0.20
Cross-sectional slope (and std. dev.) of volatility on development	-0.306 (0.035)	-0.267 (0.033)	-0.213 (0.036)	-0.173 (0.037)
Time-series slope (and std. dev.) of volatility on development	-0.487 (0.053)	-0.455 (0.059)	-0.406 (0.060)	-0.347 (0.063)
Standard deviation of log-GDP per capita in 1960	0.778 (0.066)	0.730 (0.058)	0.686 (0.057)	0.650 (0.049)
Percent variation in volatility due to a 1-std dev. increase in log GDP per capita	-23.8%	-19.5%	-14.6%	-11.3%

The table shows, correspondingly, the cross-sectional and within-country slope coefficients and standard deviations (in parentheses) from regressions of (log) volatility of annualized quarterly growth rates computed over non-overlapping decades on the average (log) level of development in the decade; a constant (not reported) is included in each regression. The cross sectional regressions are based on pooled data for 5 decades. The third set of rows shows the standard deviation of average logged GDP per capita over the whole decade (and the standard deviation over 100 simulations). The fourth line shows the percent variation in volatility generated by a 1-standard deviation increase in the logged GDP per capita. See text and notes for Table 3 for explanations.

In all, Tables 3 and $A12$ suggest that the most important dimension along which the results vary is γ, the frequency of shocks to individual varieties. As we argued in the text $\gamma = 0.1$ is a plausible value for this parameter; however, note that even relative big departures from it yield numbers that are not too farm from the empirical estimates. We conclude that the technological diversification model, while stylized, can capture the decline in volatility with development observed in the data, and the underlying mechanism seems robust to reasonable parametrizations.

D Generalizations and Extensions

D.1 Different elasticities of substitution in demand and production

In this Section we relax the assumption that the demand elasticity in equation (1) is equal to the elasticity of substitution between varieties in equation (2). Specifically, let us denote the demand elasticity by ϕ, potentially different from ε, the elasticity of substitution between varieties in equation (2).

To characterize the state of the economy, we need to keep track of the entire firm-size distribution. As we will see below, all static outcomes (wages, demand, etc.) depend only on the total number of varieties, but the evolution of the economy depends on the entire distribution. The aggregate importance of a shock to a particular variety depends on how many firms use that variety.

Firm-size distribution. Define as $m_i(t)$ the measure of firms having exactly i working varieties at time t. Let $\mathcal{M}(t) = \{m_0(t), m_1(t), m_2(t), ...\}$ denote the firm-size distribution at time t. The distribution $\mathcal{M}(t)$ sufficiently characterizes the state of the economy, both in terms of aggregate allocations and prices, and in terms of dynamics. It is important to note that $\mathcal{M}(t)$ is *random*: the firm-size distribution will depend on the realization of adverse technology shocks. Let $\mathcal{S}$ denote the set of all possible firm-size distributions.

We assume that $\mathcal{M}(t)$ follows a Markov process with deterministic trends and jumps (we later verify this to be true in equilibrium):

$$dm_i = F_i(\mathcal{M})\,\mathrm{d}t + \sum_{k=1}^{\infty} G_{ik}(\mathcal{M})\,\mathrm{d}J_k(\gamma t), \tag{A7}$$

for all $i > 0$, where $F_i : \mathcal{S} \to \mathbb{R}$ is a function capturing the deterministic change in m_i for all $i = 1, 2, ...$; $G_{ik} : \mathcal{S} \to \mathbb{R}$ is a function capturing the jump in m_i due to shock k, and the $J_k(\gamma t)$s are independent Poisson processes, each with arrival rate γ. For $i = 0$, the mass of firms is pinned down at all points in time by the free entry condition. The process starts from an initial firm-size distribution $\mathcal{M}(0) = \mathcal{M}_0$.

It will prove convenient to define the following moment of the firm-size distribution,

$$N = \int_n n^{(\phi-1)/(\varepsilon-1)} d\mathcal{M}, \tag{A8}$$

which is simplifies to the total number of varieties when $\phi = \varepsilon$.

Static decisions. A firm with n varieties produces $y(n, \mathcal{M})$ units of the differentiated good, which requires

$$l(n, \mathcal{M}) = n^{1/(1-\varepsilon)} y(m, \mathcal{M})/A(\mathcal{M}) \tag{A9}$$

workers.

Aggregate output is

$$Y(\mathcal{M}) = \left[\int_0^1 y(j)^{(\phi-1)/\phi}\, \mathrm{d}j\right]^{\phi/(\phi-1)} = \left[\int y(n, \mathcal{M})^{(\phi-1)/\phi} d\mathcal{M}\right]^{\phi/(\phi-1)}, \tag{A10}$$

where ϕ is the demand elasticity, potentially different from the elasticity of substitution across input varieties ε.

From this demand system we can derive the demand for the firm's differentiated product as

$$y(n, \mathcal{M}) = Y(\mathcal{M}) p(n, \mathcal{M})^{-\phi}. \tag{A11}$$

We have made use of the normalization that $P = 1$.

Flow profits are revenue minus labor cost, so the operating profit of the firm (before subtracting any R&D expenditures) is

$$\pi(n, \mathcal{M}) = p(n, \mathcal{M}) y(n, \mathcal{M}) - w(\mathcal{M}) l(n, \mathcal{M}) = \\ Y(\mathcal{M}) p(n, \mathcal{M})^{1-\phi} - n^{1/(1-\varepsilon)} w(\mathcal{M}) Y(\mathcal{M}) p(n, \mathcal{M})^{-\phi}/A(\mathcal{M}). \tag{A12}$$

Aggregate demand $Y(\mathcal{M})$, the wage rate $w(\mathcal{M})$ and the external effect $A(\mathcal{M})$ all depend on the state of the economy.

Bellman equation. Given the flow profit function (A12), the cost function for adoption (7), and the law of motion for $\mathcal{M}$ (A7), we can write down the Bellman equation for the firm's profit maximization problem:

$$\rho V(n, \mathcal{M}) = \max_{p,\lambda} \Big\{ \pi(p, n, \mathcal{M}) - I + \lambda n [V(n+1, \mathcal{M}) - V(n, \mathcal{M})] \\ + \gamma \sum_{i=1}^{n} [V(n-1, \mathcal{M} + \mathbf{G}_i(\mathcal{M})) - V(n, \mathcal{M})] + \\ V_{\mathcal{M}} \mathbf{F}(\mathcal{M}) + \gamma \sum_{i=n+1}^{\infty} [V(n, \mathcal{M} + \mathbf{G}_i(\mathcal{M})) - V(n, \mathcal{M})] \Big\}. \tag{A13}$$

The opportunity cost of time is compensated by flow profits (revenue minus production cost minus adoption costs) and expected capital gains. With arrival rate λn, a new variety is developed, and firm value increases. With arrival rate γ variety i is lost, and firm value drops. The last two terms capture the expected changes in value due to changes in $\mathcal{M}$ alone, holding n fixed. These changes come from the smooth changes (F), and from jumps (G).

The first-order conditions for optimal pricing and optimal adoption are

$$p = \frac{\phi}{\phi - 1}\frac{w(\mathcal{M})}{A(\mathcal{M})}n^{1/(1-\varepsilon)}, \tag{A14}$$

$$g'(\lambda)L = V(n+1, \mathcal{M}) - V(n, \mathcal{M}). \tag{A15}$$

The optimal price of the firm is a constant markup over unit cost. The unit cost decreases in the number of varieties, and increases in the prevailing wage rate. The marginal cost of increased adoption spending has to equal the marginal benefit: the potential jump in value when adoption is successful.

Constructing the equilibrium. Using the first-order condition for optimal pricing (A14), we can express a firm's operating profits as

$$\pi(n, \mathcal{M}) = \frac{(\phi-1)^{\phi-1}}{\phi^{\phi}}Y(\mathcal{M})\left[\frac{w(\mathcal{M})}{A(\mathcal{M})}\right]^{1-\phi} n^{(\phi-1)/(\varepsilon-1)}.$$

Combining equations (A9), (A11), and (A14), labor demand by firm n is

$$l(n, \mathcal{M}) = \frac{Y(\mathcal{M})}{A(\mathcal{M})}\left[\frac{w(\mathcal{M})}{A(\mathcal{M})}\right]^{-\phi}\left(\frac{\phi}{\phi-1}\right)^{-\phi} n^{(\phi-1)/(\varepsilon-1)}. \tag{A16}$$

Labor market clearing implies

$$L = \int_n l(n, \mathcal{M})d\mathcal{M} = A(\mathcal{M})^{\phi-1}Y(\mathcal{M})w(\mathcal{M})^{-\phi}\left(\frac{\phi}{\phi-1}\right)^{-\phi}\int_n n^{(\phi-1)/(\varepsilon-1)}d\mathcal{M} \tag{A17}$$

or, with the N notation

$$L = A(\mathcal{M})^{\phi-1}Y(\mathcal{M})w(\mathcal{M})^{-\phi}\left(\frac{\phi}{\phi-1}\right)^{-\phi} N.$$

Using the individual labor demand (A16), the production function (A16), and the aggregator function (A10), we can write the aggregate supply of the final good as

$$Y(\mathcal{M}) = A(\mathcal{M})^{\phi}Y(\mathcal{M})w(\mathcal{M})^{-\phi}\left(\frac{\phi}{\phi-1}\right)^{-\phi}\left[\int n^{(\phi-1)/(\varepsilon-1)}d\mathcal{M}\right]^{\phi/(\phi-1)} =$$

$$A(\mathcal{M})^{\phi}Y(\mathcal{M})w(\mathcal{M})^{-\phi}\left(\frac{\phi}{\phi-1}\right)^{-\phi} N^{\phi/(\phi-1)},$$

which allows us to express wages as

$$w(\mathcal{M}) = \frac{\phi-1}{\phi}A(\mathcal{M})N^{1/(\phi-1)}. \tag{A18}$$

Substituting this into labor market clearing (A17),

$$Y(\mathcal{M}) = A(\mathcal{M})LN^{1/(\phi-1)}. \tag{A19}$$

Substituting in (A18) and (A19) into the profit function (A12),

$$\pi(n,\mathcal{M}) = \frac{1}{\phi}A(\mathcal{M})LN^{(2-\phi)/(\phi-1)}n^{(\phi-1)/(\varepsilon-1)}.$$

We have completely characterized all static decisions. We still need to solve for V, λ, and the law of motion for $\mathcal{M}$.

Substituting in optimal pricing (A14) and equilibrium wages (A18) and output (A19), we can simplify the Bellman equation as

$$\begin{aligned}\rho V(n,\mathcal{M}) = \max_{\lambda}\Bigg\{ & \frac{1}{\phi}A(\mathcal{M})LN^{(2-\phi)/(\phi-1)}n^{(\phi-1)/(\varepsilon-1)} - g(\lambda)Ln + \\ & \lambda n[V(n+1,\mathcal{M}) - V(n,\mathcal{M})] + \gamma\sum_{i=1}^{n}[V(n-1,\mathcal{M}+\mathbf{G}_i(\mathcal{M})) - V(n,\mathcal{M})] + \\ & V_{\mathcal{M}}\mathbf{F}(\mathcal{M}) + \gamma\sum_{i=n+1}^{\infty}[V(n,\mathcal{M}+\mathbf{G}_i(\mathcal{M})) - V(n,\mathcal{M})]\Bigg\}. \end{aligned} \tag{A20}$$

Free entry. As in the main setup, free entry pins down the value of size-1 firms at

$$V(1,\mathcal{M}) = \frac{\kappa}{\eta}L,$$

independently of the state of the economy $\mathcal{M}$. We guess that the value function takes the form

$$V(n,\mathcal{M}) = v(n),$$

which can depend on n in a nonlinear way, but is also independent of $\mathcal{M}$.

$$\begin{aligned}\rho v(n) = \max_{\lambda}\Bigg\{ & \frac{1}{\phi}A(\mathcal{M})LN^{(2-\phi)/(\phi-1)}n^{(\phi-1)/(\varepsilon-1)} - g(\lambda)Ln + \\ & \lambda n[v(n+1) - v(n)] + \gamma n[v(n-1) - v(n)]\Bigg\}. \end{aligned} \tag{A21}$$

Let

$$\bar{\pi} = \frac{1}{\phi}A(\mathcal{M})N^{(2-\phi)/(\phi-1)}$$

denote the per capita profits of a size-1 firm (this is not the same as profits per variety, because profits are no longer linear in n). The value function is then the solution to the following second-order difference equation,

$$\begin{aligned}\rho v(n) = {} & \bar{\pi}Ln^{(\phi-1)/(\varepsilon-1)} - g(\lambda_n)Ln + \\ & \lambda_n n[v(n+1) - v(n)] + \gamma n[v(n-1) - v(n)], \end{aligned} \tag{A22}$$

where the optimal adoption rate λ_n satisfies

$$g'(\lambda_n)L = v(n+1) - v(n).$$

Aggregate dynamics. Given the optimal adoption intensity λ_n, we now turn to characterizing aggregate dynamics.

Recall that $m_i(t)$ is the measure of firm using exactly i varieties at time t. A certain fraction of firms of size $i-1$ are successful in adopting variety i in every instant. Similarly, a certain fraction of firms of size i are successful in adopting variety $i+1$ in every instant. As long as none of the varieties fail,

$$\mathrm{d}m_i(t) = [\lambda_{i-1}(i-1)m_{i-1}(t) - \lambda_i i m_i(t)]\,\mathrm{d}t$$

A $\lambda_i(i-1)m_{i-1}(t)$ measure of firms are going to be successful in adopting variety i, so they will become size i. A $\lambda_i i m_i(t)$ measure of size-i firms are going to be successful in adopting variety $i+1$, so they will no longer be size i.

If variety k fails, which happens with arrival rate γ, each firm using this variety will have its size reduced by one. That is, they will add to the mass of firms one below their current size. Letting $\mathrm{d}J_k(\gamma t)$ denote the failure of variety k, the jumps in m_i are

$$\mathrm{d}m_i(t) = m_{i+1}(t)\sum_{k=1}^{i+1}\mathrm{d}J_k(\gamma t) - m_i(t)\sum_{k=1}^{i}\mathrm{d}J_k(\gamma t).$$

If any of the first $i+1$ variety fails, the size-$i+1$ firms will become size i, and add to the mass of m_i. If any of the first i variety fails, then size-i firms also move down by one, and reduce m_i.

Taking the deterministic and the jump part together, and adding the notation $\mu(i) = \lambda i$ for $i > 0$ and $\mu(i) = \eta$ for $i = 0$,

$$\mathrm{d}m_i = [\mu(i-1)m_{i-1} - \mu(i)m_i]\,\mathrm{d}t + m_{i+1}\sum_{k=1}^{i+1}\mathrm{d}J_k(\gamma t) - m_i\sum_{k=1}^{i}\mathrm{d}J_k(\gamma t).$$

Indeed this law of motion is the same as (A7) with F and G properly defined,

$$F_i(\mathcal{M}) = \mu(i-1)m_{i-1} - \mu(i)im_i,$$

$$G_{ik}(\mathcal{M}) = \begin{cases} m_{i+1} - m_i & \text{if } k \le i, \\ m_{i+1} & \text{if } k = i+1, \\ 0 & \text{if } k > i+1. \end{cases}$$

for all i and k.

Clearly, if $\phi = \varepsilon$, then profits (A12) are linear in n, and the N aggregator is the total number of varieties in the economy,

$$N = \int n\mathrm{d}\mathcal{M} = \sum_{i=1}^{\infty} M_i,$$

and we are back to the baseline case.

D.2 Technological Diversification with Complementary Inputs

In this Section we show that technological diversification also operates with complementary inputs, including the case of perfect complementarity, as long as productivity shocks are not too large. We consider the same constant-elasticity-of-substitution (CES) production function,

$$y = \left[\sum_{i=1}^{n} (\chi_i l_i)^{1-1/\varepsilon} \right]^{\varepsilon/(\varepsilon-1)}, \tag{A23}$$

but we now allow for $\varepsilon < 1$. The case $\varepsilon = 0$ corresponds to Leontief technology. As before, time is continuous. Varieties can have two levels productivity, a high productivity normalized to 1, and a low productivity $\alpha < 1$. The parameter α indexes the size of productivity shocks, with lower αs corresponding to larger shocks. The benchmark model in Section II is a special case with $\alpha = 0$.[84] All varieties start out having high productivity. They face a constant hazard of being hit by a productivity shock and becoming less productive. Varieties with low productivity can never achieve high productivity again. In this sense, productivity shocks are permanent. In our notation, $\chi_i(t)$ equals 1 until time T_i, when it falls to α. T_i is the (random) date of failure of this technology. The arrival of failures for a given variety i is common to all firms using this variety, and it follows a Poisson process with arrival rate γ. Failures are independent across varieties. Substituting this productivity into the production function,

$$y = \left[\sum_{i:\chi_i=1} l_i^{1-1/\varepsilon} + \alpha^{1-1/\varepsilon} \sum_{i:\chi_i=\alpha} l_i^{1-1/\varepsilon} \right]^{\varepsilon/(\varepsilon-1)}.$$

In the hope that it will not cause confusion, we suppress the dependence on time in notation. Let n denote the overall number of varieties. Out of a total of n, k will denote the number of low-productivity varieties. It is easy to see that because all high-productivity varieties are symmetric, the same number of workers will be allocated to each. We denote the number of workers per high-productivity variety by l_H. Similarly, l_L denotes the number of workers allocated to each low-productivity variety. The production function then becomes

$$y = \left[(n-k) l_H^{1-1/\varepsilon} + \alpha^{1-1/\varepsilon} k l_L^{1-1/\varepsilon} \right]^{\varepsilon/(\varepsilon-1)}.$$

The firm employs a total of $(n-k)l_H + kl_L$ workers. Cost minimization implies that

$$\frac{l_L}{l_H} = \alpha^{\varepsilon-1}.$$

The total number of workers is then $l_H[n + k(\alpha^{\varepsilon-1} - 1)]$. Substituting in the production function, we get labour productivity as

$$\omega(n,k) \equiv \frac{y}{(n-k)l_H + kl_L} = \frac{[n + k(\alpha^{\varepsilon-1} - 1)]^{\varepsilon/(\varepsilon-1)}}{n + k(\alpha^{\varepsilon-1} - 1)} = \left[n + k\left(\alpha^{\varepsilon-1} - 1\right) \right]^{1/(\varepsilon-1)}. \tag{A24}$$

[84] We work with discrete shocks because the size of productivity shocks plays an important role in our analysis. Gaussian shocks would hide important features of technological diversification.

The notation $\omega(n, k)$ emphasizes that labour productivity depends on the number of high- and low-productivity varieties.

The firm starts with all varieties having high productivity, $k = 0$. The first productivity shock comes with Poisson arrival γn. Then k jumps to 1. The proportional drop in labour productivity is

$$\ln \omega(n, 0) - \ln \omega(n, 1) = \frac{1}{1-\varepsilon} \ln \left(1 + \frac{\alpha^{\varepsilon-1} - 1}{n}\right).$$

This clearly decreases in n for all $\alpha > 0$. A higher n makes the impact of an individual shock less important to total productivity. Note that this is true even if technology is Leontief, $\varepsilon = 0$. How could a shock become less important with Leontief technology? When the productivity of one variety falls to α, the firm increases the usage of that input by a factor of $1/\alpha$ so as to keep it at par with the rest of the complementary varieties, $l_L = l_H/\alpha$. Labour productivity falls because more workers are needed to produce the same amount of output. But the extra workers are only needed on the one variety hit by the shock, which represents a $1/n$ fraction of the total workforce. Labour productivity hence "only" drops by $(1/\alpha - 1)/n$. At the same time, a higher n increases the probability that any one of them is hit by an adverse shock. This tends to increase volatility. From Lemma 1, we can express the variance of labour productivity as

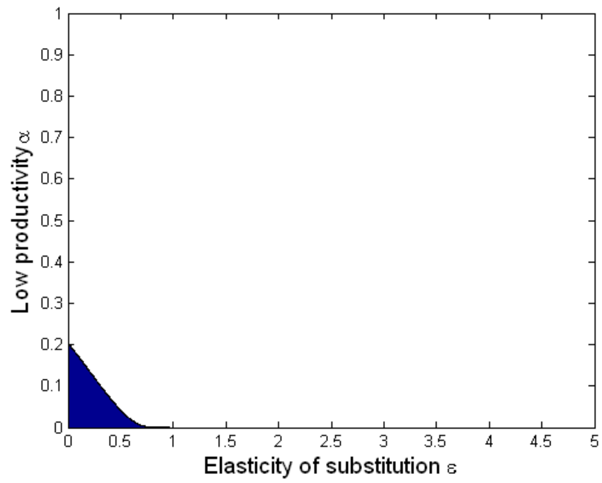
$$\text{Var}(\text{d}\ln \omega)/\,\text{d}t = \frac{\gamma n}{(\varepsilon - 1)^2} \ln^2 \left(1 + \frac{\alpha^{\varepsilon-1} - 1}{n}\right). \tag{A25}$$

We are interested in how volatility changes with n, the number of varieties used by the firm, that is, on the net effect of the two channels. We have the following proposition, which follows from differentiating A25 with respect to n.

Proposition 8. Volatility decreases in n for all $n \geq 1$ if and only if $\alpha^{\varepsilon-1} \leq 1 + \varrho$, where $\varrho \approx 3.9$ is the solution to $(1 + \varrho)\ln(1 + \varrho) = 2\varrho$.

The condition requires that either shocks are small (α is close to 1) or that complementarities are not too strong (ε is not too much lower than 1). This makes the law-of-large-numbers channel stronger than the increased likelihood of failure. If $\varepsilon > 1$, that is, the inputs are substitutes, then technological diversification prevails irrespective of the size of shocks. If, on the other hand, inputs are complements, then technological diversification works with small-enough shocks. Figure *A*7 illustrates the parameter space (non-shaded area) for which there is technological diversification. The line plots the cutoff of shock size for different values of the elasticity of substitution ε. If α is above the line, that is, if shocks are smaller than the cutoff, then volatility unambiguously declines with the number of varieties. Most notably, even if the production technology is Leontief ($\varepsilon = 0$), technological diversification will reduce volatility as long as shocks are smaller than 80 percent (that is, α is above 0.20 in the Figure). The graph shows that for $\varepsilon > 1$, technological diversification always takes place, regardless of the size of α.

Figure $A7$: Parameter Space for different ε and a



Proof of Proposition 8

First we differentiate the log of (A25) with respect to n:

$$\frac{\partial \ln \text{Var}}{\partial n} = \frac{1}{n} + 2\frac{1}{\ln\left[1 + (\alpha^{\varepsilon-1} - 1)/n\right]}\frac{1}{1 + (\alpha^{\varepsilon-1} - 1)/n}\frac{1 - \alpha^{\varepsilon-1}}{n^2}.$$

This is negative if and only if

$$1 + x < \frac{2x}{\ln(1+x)},$$

where x stands for $(\alpha^{\varepsilon-1} - 1)/n$.

Take the case when $\varepsilon > 1$. Then, $x \in (-1, 0)$ and $\ln(1+x) < 0$. Rewrite the condition as $(1+x)\ln(1+x) > 2x$. The left-hand-side is greater for all $x \in (-1, 0)$, irrespective of the values of ε, α, or n. This implies that volatility declines in n if $\varepsilon > 1$, irrespective of the size of shocks.

When $\varepsilon < 1$, $x > 0$ and $\ln(1+x) > 0$. The condition can then be rewritten as $(1+x)\ln(1+x) < 2x$ and holds for all $x < \varrho$, where ϱ is such that $(1+\varrho)\ln(1+\varrho) = 2\varrho$. This is because $(1+x)\ln(1+x)$ increases faster in x than $2x$ does. We then want

$$x = \frac{\alpha^{\varepsilon-1} - 1}{n} < \varrho$$

to hold for all $n \geq 1$, which requires $\alpha^{\varepsilon-1} < 1 + \varrho$ as stated in the Proposition.

Intuitively, even when goods are complements (in the sense of having an elasticity of substitution below 1), there can be scope for substitutability in the budget; this is similar to the result that "every good has at least one substitute," even when there is complementarity in production (see Mas Collel, Whinston, and Green (2005) for further discussion). A model in which the development process entailed *progressively lower* substitutability across inputs could counterfactually predict increasing volatility with development. (We focus the analysis on constant-elasticity models and do not study these cases.) In practice, of course, there are different combinations of substitutability and complementarity among different groups of inputs and these are not necessarily constant over time either. CES production functions are quite restrictive, but note that they at least allow for more flexibility than many models that only distinguish between labour and total capital (or an aggregate intermediate input); typically, the aggregate input or capital is implicitly defined as being proportional to the sum of all different intermediate inputs. This implies that the elasticity of substitution between intermediates is infinite. In an example from Romer (1990), an additional dollar in the form of a truck has the same effect on the marginal productivity of mainframe computers as an additional dollar's worth of computers. Infinite substitutability is an extreme assumption, and CES production functions bring in some more realism by limiting the scope for substitution (in standard calibrations).

D.3 Risk Aversion and Financial Autarky

We now discuss technology adoption when agents are risk-averse and risk pooling is not possible. Each firm is owned by a risk-averse individual, whose only source of income is the profit of the firm. Utility exhibits risk aversion with $u' > 0$, $u'' < 0$, $u(0) > -\infty$, $u'(0) < \infty$. These assumptions ensure the finiteness of the value of the firm even if there is a positive probability that the firm profits (and hence consumption) eventually become zero. The value of the firm with n varieties in state $\mathcal{M}$ is defined as lifetime expected utility,

$$V(n, \mathcal{M}) = \max_{\{p,\lambda\}} E \int_{t=0}^{\infty} e^{-\rho t} u\{\pi[n(t), \mathcal{M}(t)] - g[\lambda(t)]Ln(t)\}\mathrm{d}t \tag{A26}$$

where $n(t)$ and $\mathcal{M}(t)$ evolve according to the laws of motion (10) and (8), respectively, and maximization is subject to a nonnegative profit constraint,

$$g(\lambda) \leq \frac{1}{\varepsilon} A(\mathcal{M}) N(\mathcal{M})^{(2-\varepsilon)/(\varepsilon-1)}.$$

Flow utility at time t comes from net profits at time t (there is no borrowing and lending), and utility is discounted with subjective discount rate ρ. The Bellman equation characterizing the firm's problem is

$$\begin{aligned} \rho V(n, \mathcal{M}) = \max_{p,\lambda} \Bigg\{ u \left[\frac{1}{\varepsilon} L A(\mathcal{M}) N(\mathcal{M})^{(2-\varepsilon)/(\varepsilon-1)} n - g(\lambda) L n \right] + \\ \lambda n [V(n+1, \mathcal{M}) - V(n, \mathcal{M})] + \gamma \sum_{i=1}^{n} [V(n-1, \mathcal{M} + \mathbf{G}_i(\mathcal{M})) - V(n, \mathcal{M})] + \\ V_{\mathcal{M}} \mathbf{F}(\mathcal{M}) + \gamma \sum_{i=n+1}^{\infty} [V(n, \mathcal{M} + \mathbf{G}_i(\mathcal{M})) - V(n, \mathcal{M})] \Bigg\}. \end{aligned} \tag{A27}$$

This is the same as (12) with the exceptions that (i) flow utility is a concave function of firm profits, and (ii) we rule out borrowing so that adoption has to be financed from current profits. We next characterize adoption intensity.

Proposition 9. Optimal adoption intensity, $\lambda(n, \mathcal{M})$, is strictly positive for all $n > 0$ and $\mathcal{M}$.

The proof relies on the property that new varieties lead to higher profits. This is why firms have an incentive for technological diversification irrespective of financial markets. Of course, the *magnitudes* may vary with the degree of financial development. However, financial deepening is not *required* for the technological diversification channel to work. The result that the adoption intensity is positive for *all* n depends on the properties of the cost of adoption. In particular, the Inada conditions ensure that it is always optimal to devote some resources to adoption as long as the marginal benefit is positive. Of course, if the marginal cost of adoption is bounded away from zero, there is a range of positive but small marginal benefits for which adoption intensity will be zero. This does not alter the result that financial development is not a *necessary precondition* for technological diversification.

Proof of Proposition 9. Because $g(0) = 0$, the non-negative profit constraint provides a positive upper bound on λ. If the constraint is binding, λ is positive. Otherwise we can use the first-order-condition for optimal adoption,

$$u'\left[\frac{1}{\varepsilon}LA(\mathcal{M})N(\mathcal{M})^{(2-\varepsilon)/(\varepsilon-1)}n - g(\lambda)Ln\right]g'(\lambda)L = V(n+1,\mathcal{M}) - V(n,\mathcal{M}). \qquad \text{(A28)}$$

The properties of u' and g' ensure that there will be a unique positive λ for each n as long as $V(n+1,\mathcal{M}) - V(n,\mathcal{M}) > 0$. This condition is easy to verify. It is obvious that $V(n+1,\mathcal{M}) \geq V(n,\mathcal{M})$, because the firm can always throw away the additional variety and replicate its profits with n varieties. We can also show that it is strictly better off with more varieties.

The value of a firm with n products is $V(n,\mathcal{M})$ defined by (A26). Now calculate a lower bound for the expected discounted utility if the firm adds a variety. Suppose the firm does not change its adoption efforts but keeps them at $\lambda(n)$. Let us denote the value of this strategy by $\tilde{V}()$. It is clear that $V(x,\mathcal{M}) \geq \tilde{V}(x,\mathcal{M})$ for all x and $\mathcal{M}$, because the firm cannot lose by adjusting its adoption intensity optimally.

Now suppose that the additional variety is useless, $\tilde{V}(n+1,\mathcal{M}) = V(n,\mathcal{M})$. In this case the firm does not innovate, and is making profits $\frac{1}{\varepsilon}LA(\mathcal{M})N(\mathcal{M})^{(2-\varepsilon)/(\varepsilon-1)}$ per variety. The flow profits the additional variety generates while working are strictly positive, which ensures that profits with $n+1$ dominate profits with n in a first-order stochastic sense. Because $u' > 0$ even if the consumer is risk averse, we have that $\tilde{V}(n+1,t) > V(n,t)$, a contradiction. Hence $\tilde{V}(n+1,\mathcal{M}) > V(n,\mathcal{M})$ and $V(n+1,\mathcal{M}) > V(n,\mathcal{M})$.

D.4 Derivation of Initial Variance of Growth

The variance of real GDP growth is proportional to:

$$\sum_{k=1}^{\infty} M_k^2/N^2, \qquad \text{(A29)}$$

where

$$M_k = \sum_{i=k}^{\infty} m_i$$

is the measure of firms using variety k (they might also higher-order varieties). We need to calculate $\sum_{k=1}^{\infty} M_k^2$:

$$\begin{aligned}
\sum_{k=1}^{\infty} M_k^2 &= \sum_{k=1}^{\infty}\sum_{i=k}^{\infty}\sum_{j=k}^{\infty} m_i m_j \\
&= \sum_{i=1}^{\infty}\sum_{j=1}^{\infty} \min\{i,j\} m_i m_j \\
&= \sum_{j=1}^{\infty} j m_j^2 + 2\sum_{j=1}^{\infty}\sum_{i=1}^{j-1} i m_i m_j.
\end{aligned}$$

Some auxiliary formulas:

$$i m_i^2 = \frac{1}{\ln(1-\nu)^2}\frac{\nu^{2i}}{i}$$

so that

$$\begin{aligned}
\sum_{i=1}^{\infty} i m_i^2 &= \frac{-\ln(1-\nu^2)}{\ln(1-\nu)^2} \\
m_j \sum_{i=1}^{j-1} i m_i &= \frac{1}{\ln(1-\nu)^2}\frac{\nu^j}{j}\sum_{i=1}^{j-1}\nu^i \\
\sum_{i=1}^{j-1}\nu^i &= \frac{\nu-\nu^j}{1-\nu}.
\end{aligned}$$

Hence:

$$\begin{aligned}
m_j \sum_{i=1}^{j-1} i m_i &= \frac{1}{\ln(1-\nu)^2}\frac{\nu^j}{j}\frac{\nu-\nu^j}{1-\nu} \\
\sum_{j=1}^{\infty}\sum_{i=1}^{j-1} i m_i m_j &= \frac{-1}{(1-\nu)\ln(1-\nu)}\left[\nu - \frac{\ln(\nu-\nu^2)}{\ln(1-\nu)}\right]
\end{aligned}$$

$$\sum_{k=1}^{\infty} M_k^2 = \frac{(1+\nu)\ln(1-\nu^2) - 2\nu\ln(1-\nu)}{(1-\nu)\ln(1-\nu)^2}.$$

Dividing by the square mean, we obtain

$$\frac{\sum_{k=1}^{\infty} M_k^2}{N^2} = 2(1-1/\nu)\ln(1-\nu) - (1-1/\nu^2)\ln(1-\nu^2).$$

References for Online Supplemental Appendix

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