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The Geography of Output Volatility*

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Abstract

This paper examines the structural determinants of output volatility in developing countries, and especially the roles of geography and institutions. We investigate the volatility effects of market access, climate variability, the geographic predisposition to trade, and various measures of institutional quality. We find an especially important role for market access: remote countries are more likely to have undiversified exports and to experience greater volatility in output growth. Our results are based on Bayesian methods that allow us to address formally the problem of model uncertainty and to examine robustness across a wide range of specifications.

JEL Classifications: O11, E30

Keywords: Volatility, Geography, Institutions, Bayesian Model Averaging

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1 Introduction

This paper seeks to explain why output growth is systematically more volatile in some countries than others. Although it is possible to argue that overall volatility is gradually declining, most developing countries are still highly unstable relative to OECD members. Output volatility has long been high in sub-Saharan Africa and Latin America, and in the 1990s, instability extended even to the miracle economies of East and Southeast Asia. Sustained growth is a rare achievement, for reasons that are not fully understood, and volatility appears endemic in many poorer countries. In this paper, we examine structural determinants of volatility, and especially the competing roles of geography and institutions.

Our emphasis on the geography of output volatility is unusual. To see why it matters, consider a popular claim, that output volatility in poor countries arises largely from fluctuations in the terms of trade. Studies such as Easterly et al. (1993) and Broda (2004) draw attention to the empirical importance of these fluctuations, but do not explain why some economies are far more exposed to world price shocks than others. It is true that, from the perspective of a small open economy, changes in world prices are exogenous. But the impact of world price variation on a given economy depends on its import and export structures, and these are clearly endogenous in the long run. Our empirical work will show how export structures are partly determined by geographical characteristics, and can leave isolated countries especially prone to external shocks.

This is not the only effect we examine, and we draw on a much wider range of geographic variables than previous work. We investigate the roles of the Frankel-Romer (1999) measure of the geographic predisposition to trade, several measures of coastal access, ecological classifications of tropical location, and measures of climate variability. By looking at intermediate outcomes, we also attempt to trace out mechanisms by which geography can influence volatility. For example, we use an index of export concentration to confirm that remote countries typically export a narrow range of goods and are especially vulnerable to world price shocks. Although this relationship has been discussed informally, as in the 2003 Human Development Report (UNDP 2003), our paper quantifies the effect and shows it to be important even when conditioning on the level of development.

Sub-Saharan Africa provides a stark example of the possible links between geography and volatility. In the rest of the developing world, recent decades have seen a rapid diversification in export structures, away from primary commodities. Collier (2003) notes that in 1980, three-quarters of developing country exports were primary commodities; now roughly 80% are manufactures. This trend is much less pronounced in Africa. Competitive manufacturing exporters are so rare across the continent, even in the success stories of Botswana and Mauritius, that the explanations may lie deeper than simply weak governance or macroeconomic disarray. Continued dependence on primary commodities, high output volatility, and slow growth may reflect, at least in part, Africa's distance from large markets and poor internal transport infrastructure.

Take an admittedly extreme example, Uganda. The country has only two main passages to the sea: the Northern Corridor to the port of Mombasa, and the Central Corridor to Dares-Salam. The capital, Kampala, is 900 miles by rail from the nearest port. Although transport improvements are in progress, only about 7% of the total highway system is paved (CIA World Factbook 2002). Internal strife, including civil war, has reinforced the natural barriers to trade, and the adverse combination of geographic and political factors is reflected in a concentrated export structure: in 1995 more than two-thirds of Uganda's export earnings came from coffee. Perhaps not surprisingly, a measure of the terms of trade volatility for Uganda is close to the 90th percentile in our sample of developing countries, while output volatility is at the 75th percentile.

Moving beyond this anecdotal level, our work suggests that associations between geographic characteristics, political institutions and output volatility are systematic features of the cross-country data. The paper therefore contributes to the lively debate on geography versus institutions as competing drivers of economic outcomes, reflected in recent exchanges between Rodrik and Subramanian (2003) and Sachs (2003b), and in the empirical work of Acemoglu et al. (2001), Easterly and Levine (2003), Hall and Jones (1999), Rodrik et al. (2004) and Sachs (2001, 2003a). Our contribution is relatively systematic, in that we consider a wider range of geographic and institutional indicators than most previous studies. We are able to show that geography and institutions are both important. Once combined, they can explain as much as two-thirds of the international variation in volatility.

We have sought to improve on existing research in other ways. First, we investigate channels of influence, rather than simply presenting reduced-form partial correlations that can be hard to interpret. Secondly, previous research often uses explanatory variables, such as indicators of macroeconomic policies, that are likely to be endogenous and determined jointly with volatility by other country characteristics. This explains our emphasis on candidate explanatory variables that are either predetermined (geography) or that evolve only slowly over time (institutions). We therefore have more chance of identifying fundamental or structural determinants of volatility.[1]

A major improvement on previous work is that, as in Sala-i-Martin et al. (2004), we adopt Bayesian methods in preference to an ad hoc approach to model selection. There are several reasons for this choice, which have been well rehearsed in the empirical literature on the determinants of growth. As in the case of growth, competing theories that seek to explain volatility are not mutually exclusive, and the number of possible determinants is vast. This leads to uncertainty about the regression specification and implies that conventional methods for inference can be highly misleading. We use recently developed Bayesian

[1] At first this may seem limiting, not least because the problems of the late 1990s have often been attributed to weaknesses in domestic financial sectors and unsustainable macroeconomic policies, two factors that we do not investigate until the final empirical section of the paper. As Acemoglu et al. (2003) have argued, these problems can be seen as symptoms or equilibrium outcomes associated with more fundamental characteristics, including weak institutions.

methods to address uncertainty about the appropriate model, to lessen the need for arbitrary choices, and to provide an index of the weight of evidence in favour of specific models. The main strength of this approach is that we can consider a wide range of candidate predictors in a rigorous way.

Beyond geographic influences, we also find a strong role for political institutions, including the extent of formal constraints on the political executive. Countries with weaker institutions tend to be more volatile. Our Bayesian approach reveals the robustness of this partial correlation, and shows that it is not sensitive to the choice of regression specification. Moreover, we are able to show that the effects of geography are robust to controlling for institutional quality, and vice versa. Other fixed country characteristics that might be thought to be associated with volatility, such as ethnic diversity and religious polarization, appear to have less explanatory power.

The paper is organized as follows. Section 2 summarizes previous research on the origins and consequences of volatility. Section 3 describes the data set and introduces our main explanatory variables. Section 4 discusses the empirical strategy employed in the paper, focusing on the Bayesian approach to model uncertainty. Introducing the main results, section 5 examines the role of predetermined variables in explaining output volatility. Section 6 looks in more depth at geography, and section 7 considers the combined role of geography and institutions. Section 8 briefly considers robustness, before section 9 concludes.

2 Origins and consequences of volatility

In this section, we briefly consider the consequences of output volatility, and then review evidence on its sources. Our focus will be on empirical evidence for developing countries rather than theoretical models. Many of the relationships we study can easily be justified informally, and whether they are genuinely important is primarily an empirical question.

One perception of output volatility is that it emerges primarily in the form of economic crisis. Recent instances include Mexico in 1995, Russia in 1998, Brazil in 1999, Turkey in 2001, and Argentina in 2002. It is important to be aware, however, that volatility in developing countries is not confined to instances of crisis, but appears to be endemic. Even over a period as long as forty years, 1960-99, the median standard deviation of annual growth rates in low-income developing countries was more than three times the median standard deviation in OECD member countries.

The consequences of volatility are potentially serious. The adverse effects will be felt especially strongly by households living in poverty, who may lack the liquid wealth or access to credit that would be needed to smooth consumption. As well as being a significant source of risk for the poor, the uncertainty associated with short-run output variations can also translate into lower investment and reduced economic growth. These effects have sometimes been investigated using aggregate data. The most widely-known findings are that more volatile countries display slower growth (Ramey and Ramey 1995) and lower private investment (Aizenman and Marion 1999).[2]

Most of the explanations for volatility fall into four broad categories.[3] One strand of research emphasizes the role of openness, trade and external shocks, and especially terms of trade volatility. A second factor is domestic policy mismanagement, as reflected in high inflation, overvalued exchange rates, and sustained budget deficits. A third line of argument is that the nature of financial institutions may be relevant. Finally, more general institutional and political characteristics could play a role, especially the nature of political competition and the extent of constraints on decision-makers.

We start with a popular view of instability in poorer countries, namely that volatility in the terms of trade is largely responsible. As we indicated in the introduction, this is fine as far as it goes, but leaves much unexplained. In our empirical work, we will confirm the strong association between volatility in output and that in the terms of trade, but we also seek to explain why some countries are especially exposed to world price fluctuations, something that has rarely been attempted in previous research.

Terms-of-trade shocks will be most serious in relatively open economies. For this and other reasons, there is a common presumption that open economies are less stable, but the evidence is mixed, as discussed in Winters et al. (2004). Our empirical work will cast some indirect light on the relationship between openness and volatility, since one of the explanatory variables we consider is the Frankel and Romer (1999) measure of geographic predisposition to external trade, based on domestic population size and the proximity of large markets.

A second class of explanations for volatility is based on domestic policy mismanagement. Hausmann and Gavin (1996) suggested that distortionary macroeconomic policies, such as misalignment of exchange rates and mismanagement of fiscal and monetary policy, are a major source of instability. Fatás and Mihov (2004) argue that volatility is partly induced by discretionary fiscal policy. Agenor et al. (2000) similarly emphasize the role of policy, as well as trade. More generally, the belief that volatility and slow growth often reflect macroeconomic disarray has been a cornerstone of the policies associated with the Washington Consensus (for example, Fischer 2003).

There is growing interest in a third influence on volatility, namely the financial sector. In principle, financial sophistication could dampen output fluctuations in a number of ways, by allowing diversification, and by reducing informational asymmetries in financial markets.

[2]Aggregate production risk may also be associated with greater educational inequality and lower average attainment (Checchi and Garcia-Penalosa 2004). Other relevant work on volatility, theoretical and empirical, includes Fatás and Mihov (2004), Gavin and Hausmann (1998), Hopenhayn and Muniagurria (1996), Imbs (2002), Jeong (2002) and Turnovsky and Chattopadhyay (2003). An older literature examined the connection between export instability and growth; see Gelb (1979) for references.

[3]Our list is not exhaustive. For example, Iyigun and Owen (2004) investigate the relationship between income inequality and the volatility of consumption growth.

Access to international capital markets could allow risk-sharing and smoothing of domestic consumption. Empirically, however, the importance of these ideas remains unproven. Some studies, notably Bekaert et al. (2004), Easterly et al. (2001), Denizer et al. (2002) and Ferreira da Silva (2002) indicate that domestic financial development reduces volatility of various kinds, but the results of Beck et al. (2001) are more ambiguous.[4]

These explanations for output volatility are not mutually exclusive and may interact in various ways, especially when institutional factors are added to the list. Rodrik (1999) argues that countries are particularly vulnerable in the wake of external shocks when their mechanisms for resolving social and distributional conflicts are weak. Acemoglu et al. (2003) have argued that the correlation between policy mismanagement and volatility can be explained in terms of institutional weaknesses that predispose some countries towards high volatility and macroeconomic policy errors. We discuss the more general role of institutions below.

The existing literature has rarely acknowledged the potential importance of geography for output volatility. Geography arguably deserves more attention as an explanation for underdevelopment, not least given the strong association between tropical location and underdevelopment most recently emphasized by Sachs (2003a). The problems faced by tropical countries include remoteness from large markets, higher incidence of disease, poor natural resource endowments, and climatic factors. These and other considerations have been highlighted in the work of Diamond (1997) and Gallup, Sachs and Mellinger (1999) but the consequences of geographical characteristics for volatility are not well understood. As a first look at the data, figure 1 shows the average extent of volatility (measured by the standard deviation of annual growth rates) for groups of countries within different latitude bands. Countries nearer the equator experience higher volatility.

The mechanisms linking geography and volatility may not always be straightforward. For example, countries that are landlocked or distant from large markets can be less exposed to external shocks, precisely because these natural barriers tend to limit trade. At the same time, if a lack of market access inhibits trade, it can also lead countries to specialize in a relatively narrow range of exports, often primary commodities. These countries will be especially vulnerable to changes in world prices. Hence, the geography of market access can determine the extent of trade and the structure of imports and exports, and these effects on volatility may operate in opposing directions.

One reason for primary commodity dependence is that distance imposes high transport costs. Ocean shipping is still one of the cheapest modes of transportation and, by increasing the costs of sea transport, geographic distance acts as a structural barrier to trade. This effect is familiar from the empirical success of gravity models of trade, in which bilateral trade

[4]The effects of opening the capital account are especially unclear. The experience of the 1990s suggests that this can be associated with greater domestic volatility, given the possibility of swift reversals in short-term capital flows. For relevant theoretical work see Aghion et al. (2004), Martin and Rey (2002) and Uhlig and Scott (1999).

flows are inversely related to an increasing function of distance. Looking directly at shipping costs, Radelet and Sachs (1998) found that the average cost of freight and insurance for landlocked developing countries was about 50% higher than for coastal countries.

When the production of labour-intensive manufactured exports is associated with a high import content and small profit margins, natural barriers to trade can make domestic production uncompetitive. This tends to imply that geographically remote countries will find it harder to develop non-primary exports, and especially manufacturing goods. Geographic remoteness can also prove a barrier to more general forms of integration into the world economy. In principle, it can reduce the efficiency of supply chains and limit the flow of ideas and technology, especially where this depends on interactions between individuals and firms in different countries.[5]

The cumulative effect is that countries that are geographically isolated, or that have only limited access to coasts and ocean-navigable rivers, could face especially strong barriers to development. Breinlich (2005) has recently drawn attention to the correlation between proximity to large markets and the relative size of the manufacturing sector in poorer countries. Radelet and Sachs (1998) argue that there is a strong link between high shipping costs and slow growth of manufactured exports. Redding and Venables (2003) attribute the weak export performance of sub-Saharan Africa partly to geographic characteristics. In our work, we examine in more detail how geographic barriers to trade can lead to export concentration, vulnerability to external shocks, and output volatility.

Our second theme is the role of institutions in determining the extent of volatility. Some features of institutionally weak societies, including greater infighting between contending groups and a shifting balance of power, could be associated with economic instability (Acemoglu et al., 2003). In countries with participatory political structures, it may be easier to build a consensus for political or economic reforms, or in response to an external shock (Rodrik 1999, 2000). In democracies, the need to obtain general political backing for policy decisions can also imply that extreme or risky policies are less frequent than under autocracy; in particular, bad policies are more likely to be weeded out under democracy. Hence, democracy may be associated with less variable outcomes than autocracy, both across countries and over time. Almeida and Ferreira (2002) present evidence that favours this hypothesis.

A closely related aspect of political institutions is the extent of formal constraints on the executive. In principle, the effects of constraints could go either way. Political structures with constraints on executive discretion may be less susceptible to dramatic policy shifts and arbitrary decision-making, and associated with reduced uncertainty. Alternatively, such constraints may preclude a flexible policy response at a time of crisis. Whether the benefits of constraints on executive discretion outweigh the costs of lost flexibility is primarily an

[5] See Overman, Redding, and Venables (2003) for a more general discussion of the links between geography and trade, and Redding and Venables (2004) for estimates of a structural model that links development levels to market access.

empirical question, and one that we will investigate in section 7. Related work includes Fatás and Mihov (2004), Gaviria et al. (2004) and Henisz (2000, 2004).

3 The sample and variables

In this section, we describe the sample of countries and the most important variables used in our empirical work, and briefly outline the recent patterns in output volatility. We take the population of interest to be the countries of the developing world. Our main sample has 70 developing countries, but sometimes we also report results for a smaller sample (those developing countries for which settler mortality data are available, 57 countries) and a sample of 88 countries which also includes high-income OECD member states. We always exclude transition economies and countries with a population of less than one million in 1960. A more detailed list of the countries, variables and data sources is contained in Appendix 2.

Our measure of volatility is the standard deviation of the annual growth rate of GDP per capita over 1960-99. The GDP data are taken from release 6.1 of the Penn World Table, due to Heston, Summers, and Aten (2002). We use the chain-weighted real output series named RGDPCH in PWT 6.1, and measure annual growth rates using log differences. The measure of output volatility is denoted by *VOL* throughout the paper and tables.

The standard deviation of annual growth rates is easy to interpret, but we should briefly note some limitations. In principle a measure of volatility should be based on explicit assumptions about the relative costs of variation at different frequencies (Gelb 1979). For example, output volatility at very short horizons may be inherently less costly than at longer horizons. Gelb recommends estimating the spectrum of the relevant time series (such as annual growth rates) and giving more weight to fluctuations at certain frequencies. In practice it is hard to identify an appropriate weighting scheme, and all commonly used volatility measures embody arbitrary assumptions. This is true of the standard deviation of annual growth rates, but as shown by Tsui (1988), also of measures that are based on the unpredictable component of a time series, for example by modelling the growth rate as an ARMA process and using an estimate of the variance of the error term.

Although some researchers assume that uncertainty (unpredictable variation) is always of primary interest, there are at least two good reasons for focusing on volatility rather than uncertainty. First, some costs of output variation will be incurred even if the variation is anticipated, especially if the possibilities for consumption smoothing and other behavioral responses are limited by market incompleteness and credit constraints. Second, the measurement of uncertainty relies on a specific forecasting model, usually a simple autoregressive model for growth rates. In practice, given that annual growth rates are not strongly autocorrelated, the two approaches are unlikely to differ greatly in practice.

Our main dependent variable, the standard deviation of growth rates, is necessarily non-negative, and so a transformation may be desirable. For simplicity, we focus on linear models for the majority of the paper, but we also investigate models where the dependent variable is a nonlinear (Box-Cox) transformation of the standard deviation of growth rates. We estimate these nonlinear models using maximum likelihood and discuss these alternative results in section 8.

We now discuss our main explanatory variables. We tend to emphasize variables that are either predetermined, slow to evolve, or plausibly exogenous. We sometimes condition on population size in 1960 (*POP60*). If agents are subject to both common and idiosyncratic income disturbances, the volatility of aggregate income will initially decline quickly with population size, but will then reach a lower limit depending on the volatility of the common component (Canning et al. 1998). In practice, this relationship is likely to be dominated by the inverse relation between population size and openness to trade, driven by the extent of opportunities for internal trade. Small states often have relatively high trade shares and concentrated export structures, which can make them especially vulnerable to external shocks, as discussed in Easterly and Kraay (2000).

Another conditioning variable we sometimes use is the level of GDP per capita in 1960, measured in PPP terms. This allows us to address the concern that, in examining the relationship between volatility and variables such as export concentration, the latter could be acting simply as proxies for the level of economic development. There are also theoretical models, notably Acemoglu and Zilibotti (1997) and Koren and Tenreyro (2004), which suggest that volatility should be negatively associated with the level of development.[6]

One key variable in our analysis is volatility in the terms of trade. We measure this using the standard deviation of log first differences of the terms of trade index, from the World Bank's World Development Indicators. In principle, it is possible to construct a measure of real national income which adjusts for changes in the terms of trade, and therefore compute a direct effect of such changes as in Kohli (2004). In this paper, however, we are more interested in such volatility as an indicator of external shocks. The domestic effects of shocks can be strongly amplified or diminished by policy responses, as discussed in Collier (2003), not least because world price shocks tend to destabilize the government budget. We therefore consider the overall relationship between long-run volatility in growth rates and in the terms of trade, rather than simply the direct effect of price changes on real income.

Another important component of our empirical work is a measure of export concentration constructed by UNCTAD, which we call *EXCON*. This is a modified version of a Herfindahl-Hirschmann index, and is defined as follows:

$$EXCON = \frac{\sqrt{\sum_{j=1}^{N}(E_j/E)^2 - \sqrt{\frac{1}{N}}}}{1 - \sqrt{(1/N)}}$$

[6]For some parameter values, the Acemoglu and Zilibotti (1997) model suggests that the relationship between volatility and the capital stock may follow an inverse-U, with volatility highest at an intermediate level of development. See p. 728 of their paper.

where exports are disaggregated into N products (239 three-digit SITC product categories in the UNCTAD measure) indexed by j, E is the total value of exports, and E_j is the value of exports of product j. By construction *EXCON* lies between 0 to 1, where zero indicates that all products account for an equal share $(1/N)$ of exports by value, and figures close to one indicate that exports are dominated in value terms by a narrow range of goods. The variable we use is an average of the UNCTAD measure for the years 1980-2000.

To capture a country's natural propensity for external trade, we use the log of the geography-based trade share from Frankel and Romer (1999). This variable, which we call *FRTRADE*, is derived by Frankel and Romer from a bilateral trade equation that controls for population, land area, and distance. High values of the Frankel-Romer measure indicate that a country is relatively likely to engage in external trade, either due to proximity to large markets, or a small domestic population and therefore fewer opportunities for internal trade.

In order to assess the role of geography in more detail, we make extensive use of data made available by Harvard University's Center for International Development. We experiment with variables measuring three key geographical dimensions: tropical versus temperate location, proximity to markets and coastal access, and variables affecting agricultural performance, such as climate and soil quality. We have also experimented with measures of disease ecology, based on malaria incidence, but these lacked explanatory power.

In the empirical growth literature, the tropics have often been defined using distance from the equator as in Hall and Jones (1999), or a zero-one dummy for tropical location. As emphasized by Sachs (2001), a potentially useful alternative is to define the tropics on an ecological rather than a geographical basis. Measures of the ecological tropics account for temperature, precipitation, growing season, natural vegetation, cover and other characteristics. We make use of two well-known ecozone classification systems of the tropics, namely the Holdridge zones and the Koeppen-Geiger (KG) zones. These classifications define climatic boundaries based on vegetation types, temperature, and precipitation. The variables we consider include *KGPTEMP* (the share of a country's population that lives in a Koeppen-Geiger temperate zone), *ZTROPICS* (the percentage of total land area in the ecological tropics), and *ZDRYTEMP* (the percentage of total land area in the dry temperate zone).

We place especial emphasis on various measures of coastal access. These include *DISTCR*, which is the log of mean distance from the nearest coastline or sea-navigable river, *POP100KM*, which is the 1994 share of population within 100km of the coast, and *POP100CR*, which is the 1994 share of population within 100km of a coast or navigable river. Note that these are not measures of population density, which would have the dimensions of people divided by area, but instead capture the extent to which the majority of the population lives within relatively easy reach of the coast. As we discuss later in the paper, proximity of the population to a coast or ocean-navigable river appears to be robustly associated with greater export diversification and less output volatility.

For climate variability, we make use of direct measures recently developed at the Columbia University's Earth Institute, and especially two indices of precipitation anomalies which we call *CMAP3* and *IND2RMS*. To capture the effect of climate variability and soil conditions on agricultural productivity in more depth, we also use indicators of soil suitability based on data from the Food and Agricultural Organization (1995). Our measure *SOILSUIT* is an estimate of the extent to which soils are moderately suitable for rain-fed crops.[7]

In examining the role of institutions, we employ a number of institutional indicators that are averaged over the sample period. One variable we use is *KKZ*, a broad index of the quality of governance formed by averaging across six measures of voice and accountability, political stability and the absence of violence, government effectiveness, regulatory burden, rule of law, and freedom from graft (Kaufmann et al., 1999). A high value of the index corresponds to high quality governance.

For some purposes, it can be objected that a measure like *KKZ* does not measure "institutions" directly. Instead, these measures reflect institutional strength as manifested in a set of outcomes, such as lack of corruption. Glaeser et al. (2004) criticize some commonly used measures of institutions on this basis. Given a conception of institutions as "the rules of the game", it may be preferable to measure directly the presence or absence of long-standing constraints. For this reason, we also experiment with narrower definitions of institutions, including *PCI*, a measure of constraints on the executive introduced by Henisz (2000). This incorporates information on the number of independent government branches with veto power.

Other variables include an alternative measure of constraints on the executive (*EXEC*) and the competitiveness of political participation (*COMP*), both from the *POLITY IV* database compiled by Jaggers and Gurr (1995). *EXEC* has been used in previous work on volatility by Acemoglu et al. (2003). *COMP* aims to capture the extent to which non-elites are able to access institutional structures for political expression. We also use a measure of the type of government (*GTYPE)* suggested by Londregan and Poole (1996), defined as the difference between the democracy and autocracy scores from the *POLITY IV* database. High values of *GTYPE* correspond to more democratic countries. Finally, because of the evidence in Acemoglu et al. (2001) that differences across countries in the mortality rates of colonial settlers may have influenced the path of institutional development, we also experiment with one of their measures of settler mortality (which we call *SETMORT*).

We also experiment with some other structural characteristics, beyond geography and institutions. These include measures of ethnic fractionalization (*ETHNIC)* and religious

[7]The soil suitability indicators are provided by the Center for International Development at Harvard University. These measures of soil quality are ultimately derived from the landmark FAO Digital Soil Map of the World, Version 3.5 (1995) and based on 7000 soil types contained in the digital map. The indicator we use is an assessment of the average extent to which soils are moderately suitable for rainfed crops, and is denoted by `soilsui2` in the CID agricultural measures database.

fractionalization, both obtained from Alesina et al. (2003). We also use the volatility of trading partner growth rates *(TPVOL)* from the Global Development Network growth database, to examine possible contagion effects associated with major shocks.

We now briefly describe the recent patterns of output volatility. Over the period 1960-1999, sub-Saharan Africa consistently experienced the highest volatility among the world's major regions, followed by Latin America, and the MENA (Middle East and North Africa) region.[8] Countries in the tropics have experienced higher output volatility than those in temperate regions, regardless of whether tropics are defined on a geographical or an ecological basis. A classification of countries by export specialization shows that exporters of primary commodities experienced relatively high volatility. We show this pattern in figure 2, which plots the median of a ten-year rolling standard deviation of growth rates for two country groups, exporters of primary goods and exporters of manufactures.

The decade-to-decade pattern indicates that volatility has generally declined, as found by Prasad et al. (2003).[9] To some extent, this pattern is also visible in figure 2. Overall, both developing and developed countries have witnessed a modest secular decline in volatility, although median volatility in the low-income countries then rose somewhat in the 1990s. The rankings of tropical and non-tropical countries, low-income and high-income countries, and primary and manufactures exporters are preserved over time. This is consistent with a maintained assumption of the paper, namely that some countries are systematically more volatile than others over long spans of time.

4 Empirical strategy

We now sketch the approach we use to analyze the sources of volatility, emphasizing the Bayesian approach to model uncertainty. The reason for choosing Bayesian methods is that empirical research on output volatility clearly faces a challenge similar to that on economic growth. There are many candidate predictors, and the relevant economic theories are open-ended in the sense of Brock and Durlauf (2001), because explanations for output volatility are not mutually exclusive. Since theory provides only weak guidance on the specification of a regression, there is uncertainty about the appropriate model.

The traditional response to this uncertainty is to downplay it, especially in conducting inference.[10] Empirical researchers often select a model and then proceed to report findings as if this model had generated the data. This procedure will typically lead researchers to understate the true degree of uncertainty about parameter estimates and the relevance of particular variables. To put this differently, if other candidate models cannot be ruled out,

[8] We provide more details of these stylized facts in the working paper version of this research.

[9] Since one component of the volatility of growth rates will be temporary measurement errors in real GDP, the secular decline in volatility may partly be an artifact of better output measurement.

[10] The main exception is the line of growth research that uses Leamer's extreme bounds analysis or variants upon it, following the influential work of Levine and Renelt (1992).

the true degree of uncertainty about the parameters will usually be greater than the standard errors of a single regression imply.

Another criticism of standard procedures is the reliance on significance tests, not least because conventional probability thresholds embody assumptions about the relative costs of Type I and Type II errors that are arbitrary and potentially inappropriate to the problem at hand. Ideally, information about parameters should feed into a tightly-specified decision problem, with an explicit objective function for the decision-maker, such as minimization of expected losses. This is hard to implement, but standard hypothesis testing procedures evade this difficulty only at first glance. As discussed in Brock and Durlauf (2001) and Brock et al. (2003), standard procedures correspond to implicit decision rules that are often unattractive.

If we acknowledge that the underlying data generating process is inherently unknowable, conventional methods for arriving at a preferred model can look arbitrary. This is especially so when the number of candidate models is large. Say that we restrict ourselves to linear regression models with explanatory variables drawn from a set of p possible predictors, where p is less than the number of countries, and where models always contain an intercept. There are 2^p possible models that could be estimated (including the null model, with only an intercept). If we also consider models that are linear in parameters but non-linear in the variables, the range of possible models becomes even larger. Even for moderate values of p, it is clear that a non-automated model selection procedure cannot be exhaustive, and will chart a course that is to some extent arbitrary. Different researchers may arrive at different conclusions, even when using similar approaches to model selection. At worst, the range of possibilities allows a dishonest researcher to mine a data set until a desired conclusion is obtained.

For all these reasons, it is clear that model uncertainty is a fundamental problem for empirical research in social science. This point was forcefully emphasized in Leamer (1978). Recent advances in computing power, and work on the problem by authors such as Raftery (1995) and Sala-i-Martin et al. (2004), have made a Bayesian approach increasingly easy to adopt. Our study is the first to apply these methods to the examination of the determinants of output volatility.

Sala-i-Martin et al. (2004) provide a clear and accessible introduction to the Bayesian approach, and we discuss the main ideas only briefly. Recall that Bayesians treat parameters as random variables, and aim to summarize uncertainty about these parameters in terms of a probability distribution. The natural extension to model uncertainty is to regard the identity of the true model as unknown, and summarize our uncertainty about the data generating process in terms of a probability distribution over the model space. By explicitly treating the identity of the true model as inherently unknowable, but assigning probabilities to different models, it is possible to summarize the 'global' uncertainty about parameters incorporating model uncertainty.

We consider the case of K possible models, and assume throughout that one of these models generated the observed data D, an assumption we discuss in Appendix 1. We denote the models by $M_1 ... M_K$ and their corresponding parameter vectors by θ_k. The Bayesian approach to model uncertainty is to assign a prior probability to each model, $p(M_k)$, as well as a prior probability distribution $p(\theta_k \mid M_k)$ to the parameters of each model.[11] Using this structure a Bayesian can then carry out inference on a quantity of interest, such as a slope parameter, by using the full posterior distribution. In the presence of model uncertainty, this distribution is a weighted average of the posterior distributions under all possible models, where the weights are the posterior probabilities that a given model generated the data (Leamer 1978).

To illustrate in the case of just two possible models, the full posterior distribution of a parameter of interest Δ can be written as:

$$p(\Delta \mid D) = p(\Delta \mid D, M_1)p(M_1 \mid D) + p(\Delta \mid D, M_2)p(M_2 \mid D)$$

Here $p(\Delta \mid D, M_k)$ are the conventional posterior distributions obtained under a given model and the terms $p(M_k \mid D)$ are the posterior model probabilities, namely the probability, given a prior and conditional on having observed D, that model M_k is the one that generated the data.

This approach requires the evaluation of posterior model probabilities, something that we discuss in Appendix 1. Briefly, as in Raftery et al. (1997) and Sala-i-Martin et al. (2004), we use the Bayesian Information Criterion (BIC) of Schwarz (1978) to approximate the Bayes factors that are needed to compute the posterior model probabilities. We can then implement a systematic form of model selection, and conduct inference in a way that acknowledges model uncertainty. For example, we can easily investigate the hypothesis that a slope coefficient β_z is non-zero, by summing the posterior model probabilities for all models in which $\beta_z \neq 0$. We can also assess the weight of evidence that a coefficient is strictly positive, by summing the posterior model probabilities for all models in which $\beta_z > 0$, and so on.[12]

An important objection to model averaging is that parameters are assumed to have the same subject-matter interpretation, regardless of the model they appear within. In many economic contexts this assumption is unattractive. To give a concrete example from our empirical work, export concentration may be a strong candidate for explaining output volatility,

[11] One interpretation of this could be that Nature draws a model from a range of possibilities and then, once the model is revealed, chooses a set of associated parameter values from a range of possibilities. This interpretation in terms of random Nature is not essential to the Bayesian approach, however. The Bayesian treatment of the unknown parameters, and the unknown identity of the true model, is more usually understood in terms of subjective uncertainty characterized relative to the statistician investigating the data. See Brock et al. (2003, p. 265) for more discussion of this point.

[12] A natural extension would be to sum the posterior model probabilities of all models in which the standardized (beta) coefficients exceed a prespecified threshold, thus giving information on which effects are robust in terms of economic significance. This is subject to the usual qualification that a variable may be important but show little variation in the data at hand.

but conditioning on this variable will hide effects of geography that work through export concentration. We therefore carry out additional model averaging exercises in which intermediate outcomes are excluded, or in some cases used as a new dependent variable.

The issue of parameter interpretation is not a trivial one. Bayesian methods can be used as part of a wider statistical analysis, including an iterative process of model building and model selection. In our empirical work, we use the Bayesian approach to isolate variables that have a high posterior probability of inclusion, and to identify parsimonious models that have high explanatory power, as reflected in the posterior model probability. Because of the difficulty of interpreting parameters in economic terms when the conditioning variables differ across models, we do not present the full posterior distributions of the parameter estimates or even the posterior means, but instead report OLS estimates of models that are representative of those with high posterior probability.

The Bayesian approach to model uncertainty provides an index of model adequacy, the posterior model probability, which is easy to evaluate and reveals the extent of model uncertainty. As discussed by Sala-i-Martin et al. (2004), it can be used to evaluate robustness to alternative specifications while assigning less weight to competition from weak models. But many of our results can also be understood in terms of the classical (frequentist) tradition, as a systematic form of model selection in which BIC is used in preference to other criteria, and many candidate models are considered. For the precise details of how we compute posterior model probabilities and a lengthier discussion of the necessary assumptions, see Appendix 1.

5 A first look at geography and volatility

Our empirical work is based on candidate variables that are either fixed characteristics, or that evolve only slowly over time. These include aspects of geography and trade, and other characteristics such as ethnic diversity. Given that volatility is likely to be higher for small states (Easterly and Kraay, 2000) and countries at lower levels of development (as in Acemoglu and Ziliboti, 1997) we sometimes condition our empirical analysis on the initial level of income and population size.

We will begin by emphasizing geographic determinants of volatility; the role of institutions will be considered later in the paper. In our first set of results, the dependent variable is output volatility (*VOL*) measured over the period 1960-1999. In our main sample of developing countries, we have 70 observations and, to start with, a total of 23 possible explanatory variables. Using the methods described in Appendix 1, we compute posterior probabilities of inclusion, namely the sum of posterior model probabilities for all models in which a variable appears. We also provide some indication of the sign of a relationship, based on the total posterior probability for models in which a variable acts in a given direction (say, positive). The results are shown in Table 1.

In columns (1)-(3) and (5) we condition on initial population size and initial GDP per capita, finding effects of both variables. The results in column (1) immediately highlight the possible role of geography. In particular, mean distance from the coast or an ocean-navigable river (*DISTCR)* and/or its square (*DISTCR2*) receives a high posterior probability of inclusion. The dummy variable for land-locked countries (*LANDLOCK*) also appears to be an important predictor of volatility. We discuss these results in more detail later in this section.

There is also a role for a dummy variable for engagement in an external war, entered separately and interacted with the ethnic fractionalization index. We introduce these effects in column (2). The interaction term suggests that the consequences of external war for volatility are more pronounced in ethnically fragmented societies. This may be predominantly an African effect, where prolonged conflict has been associated with many forms of economic disruption (see Collier 1999).

In column (3) we add the terms of trade volatility (*VTOT)* to the list of candidate predictors. We find that this variable should be included with probability one, and therefore has explanatory power for output volatility regardless of the choice of conditioning variables. This finding is consistent with the traditional view that external shocks are fundamental to explaining volatility in poorer countries. With the inclusion of *VTOT,* a slightly different set of geographic variables emerges as important. The evidence for inclusion of mean distance to the coast and its square (*DISTCR* and *DISCTCR2)* is weaker, but these variables are supplanted by a measure of the share of population near the coast, *POP100CR*.

Note that compared with these specific geographic characteristics, more general measures such as distance from the equator (*EQDIST*) or a dummy variable for geographical tropics (*TROPICAL*) appear relatively unimportant. This supports the view of Sachs (2001) that it is preferable to use direct measures of climate, location and market access, rather than simply distance from the equator. The effect of *POP100CR* is robust to excluding initial income and population size *(*column 4*)* at which point the natural openness measure (*FRTRADE*) appears to pick up some of the effects of country size. The geographic effects are also robust to adding OECD member countries to the sample (column 5).

Looking through Table 1 as a whole, other variables appear to have only limited explanatory power. For example, an index of precipitation anomalies (*CMAP3)*, ethnic diversity (*ETHNIC*) and the eco-zone classifications (*ZDRYTEMP* and *ZTROPICS*) typically have a low probability of inclusion. This is also true of most of the regional dummies, the exception being that for South Asia, a region that appears to be less volatile than its characteristics would predict.[13]

In addition to the posterior probabilities of inclusion, the BMA procedure can be used to rank models in terms of their explanatory power, using the posterior model probabilities. As an illustration, Table 2 reveals the structure of the ten models with the highest posterior

[13]The South Asian countries in our sample are Bangladesh, India, Nepal, Pakistan and Sri Lanka.

probabilities. These models all have between six and nine regressors. Note that the extent of model uncertainty is considerable, and the top 10 models have a combined posterior probability of less than 40%. Although much higher than the prior probability assigned to any set of 10 models, this indicates that a more conventional analysis could be somewhat misleading.

We now consider the effects identified above in more detail, using OLS to estimate some of the best performing models. The results are shown in Table 3.[14] This Table has to be interpreted cautiously because, as always where model selection is involved, there will be a selection bias in the coefficient estimates. Formally, this bias is the difference between the unconditional expected values of the parameter estimates, and the expected values that obtain when the data satisfy the conditions necessary for the selection of a particular subset of variables. In our application, the coefficients and t-statistics are likely to be biased away from zero. There is no wholly satisfactory resolution to this problem, which is also a well-known feature of more ad hoc approaches to model selection (see Miller 2002, chapter 6).

Throughout, we condition on the initial level of development and initial population size. We obtain the usual result that larger economies, in terms of either GDP per capita or population size, are less volatile. The table reveals strong effects of the geographic variables, as can be seen from the standardized (beta) coefficients in the lower section of the table. When a large share of population is near the coast or navigable river (*POP100CR*) or the squared mean distance to the coast is low (*DISTCR2*) countries are less volatile. Given that the concentration of population in coastal areas may be endogenous, we replace *POP100CR* with *LND100CR*, which measures the proportion of a country's total land area within 100 km of the ocean or ocean-navigable river. As the results in column (8) show, coastal access seems to matter even when using this land-based measure.

These effects need to be interpreted with some care, because of the presence of the dummy variable for landlocked countries (*LANDLOCK*). This variable has a negative and statistically significant coefficient when the regression includes the coastal population variable, *POP100CR*. It is important to account for the combined effect of these two variables, rather than consider them in isolation. There are fourteen landlocked countries in our sample, and for 13 of these countries, *POP100CR* is below 0.10.[15] If we look at the combined effect based on the regression coefficients, we find that volatility is lowest in countries where the majority of people are near the coast (where *POP100CR* is high), intermediate in the landlocked countries, and highest in countries which are not landlocked but where a large fraction of the population is located far from the coast or a navigable river. Countries

[14]Throughout the paper, we report robust t-statistics based on the MacKinnon and White (1985) HC3 adjustment for heteroskedasticity. These t-statistics are almost always lower than under the more standard White (1980) correction, which may not be well suited to small samples.

[15]The exception is Paraguay, but excluding this country from our regressions does not affect our main results; details available on request.

in this latter category include Cameroon, Iran, Jordan, Kenya, Mauritania, Pakistan, the Republic of Congo, and Tanzania.

In columns (3)-(8) we include terms-of-trade volatility, *VTOT*. As can be seen from the standardized coefficients, a one standard deviation change in *VTOT* translates into a change of around 0.30 of a standard deviation of our volatility measure. The inclusion of *VTOT* weakens the effects of *POP100CR*: compare the standardized coefficients for this variable in columns (2) and (3). This supports our view that the association between coastal access and output volatility works partly through increased exposure to world price shocks. Coastal access remains significant even when conditioning on *VTOT*, however. A possible explanation is that lack of coastal access leads to primary commodity dependence. This may have adverse effects beyond those on the terms of trade, including greater risks of weak governance and civil war (Collier 2003).

Table 3 also shows a possible nonlinear effect for external war: there seems to be a differential effect of war in more ethnically fragmented societies. At the 75th percentile of ethnic diversity, an external war raises the standard deviation of annual growth by almost two percentage points. This result should be regarded with caution, because interaction terms are likely to be fragile when estimated from a data set of the present size.

The inclusion of regional dummies in columns (6) to (8) increases the standard errors on some of the variables, but the results are qualitatively similar. Conditional on the set of included regressors, none of the regional dummies, with the possible exception of that for South Asia, have explanatory power. Overall, these models explain about 60% of the cross-sectional variation in long-run output volatility. Added-variable plots (not shown) suggest that the highlighted effects are not driven by a handful of observations.

6 Coastal access and export concentration

We argued in section 2 that natural barriers to trade, such as distance from the coast and shipping routes, can influence specialization and export diversification. We now discuss this argument in more detail, to explain why isolated countries might specialize in narrow export categories, often primary commodities, and therefore experience higher output volatility.

The strong association between coastal locations and economic development is discussed in Smith (1776) and persists to the present day. In the USA, economic activity has been concentrated close to the ocean and Great Lakes coasts, with this pattern even increasing over the 20th century (Rapport and Sachs, 2003; see also Ades and Glaeser, 1999). In Western Europe, navigable rivers have been a focus for economic development, as in the concentration of industry around the Rhine. The surge in China's foreign trade and industrialization in the late 18th century was facilitated by the development of Treaty Ports (Eastman, 1988). Much of China's recent industrial development is concentrated on its eastern coast, and especially within the Pearl River Delta.

The importance of manufacturing in these examples is unlikely to be an accident. Regional differences in the extent of manufacturing development arise naturally in new economic geography models with transport costs and varying distances between markets, as in Breinlich (2005). Manufacturing often involves a high import content, and productivity improvements may sometimes depend on the capacity to export to world markets. This helps to explain why competitive manufacturing industries are so rare in sub-Saharan Africa, given that African countries are remote from external markets and often have poor internal transport infrastructure. As noted in the introduction, while other regions of the developing world have rapidly diversified away from primary commodities since 1980, Africa has not. This is consistent with the view that adverse geography has posed especial problems for Africa (Bloom and Sachs 1998, Wood 2003).

External trade may be especially difficult for landlocked countries. Their trade is sometimes constrained by poor transport networks in neighboring countries, and the effects of political conflict.[16] For example, two decades of civil war in Mozambique has forced a large part of the South African Development Community's trade to the port of Durban in South Africa. Malawi's trade has been rerouted from the ports of Beira and Nacala to Durban and Dares-Salam, roughly doubling transport costs. Amjadi and Yeats (1995) estimate that net freight payments to foreign nationals absorbed 11% of Africa's export earnings in 1961 and 15% in 1995. For landlocked African countries, freight cost ratios can exceed 30%.

Given high internal and external transport costs, it is easy to see how poor countries can remain locked into concentrated export structures, with exports often dominated in value terms by a narrow range of primary commodities (Ng and Yeats, 2003). Our introduction gave the example of Uganda; another is Zambia, with a mean distance from the coast that is just under 1000 kilometres. Weak transport infrastructure and the civil war in Angola have further added to transport costs, and exports are dominated by copper and other minerals. Zambia has one of the highest export concentration indices in the world (0.84) and output volatility is close to the median among developing countries.

In this section, we move beyond anecdotal evidence, and examine more directly the relationship between coastal access, export concentration and world price shocks. We began by considering models in which terms of trade volatility (*VTOT)* is the dependent variable. Table A1 in our working paper contains the relevant results, and shows that relatively few variables have explanatory power for *VTOT*. The squared mean distance to the coast (*DISTCR2)* is one of the best performers, but has a posterior probability of inclusion of just 0.39. More promisingly, we find that the UNCTAD export concentration index *EXCON* is a strong predictor of terms of trade volatility, also illustrated by the scatter plot in Figure 3.

We report the outcome of a Bayesian approach to the modelling of *EXCON* in Table

[16]The problem is compounded by administrative costs in the form of transit and custom charges, and the hidden costs of bribes and administrative delays. See Anyango (1997) and Snow et al. (2003) for more on freight costs when transit countries are involved.

4.[17] From the posterior probabilities of inclusion reported in the table, it is clear that geographical characteristics and export concentration are strongly associated. Columns (1) and (2) show that coastal distance (*DISTCR2 , DISTCR*), the Frankel-Romer natural openness measure (*FRTRADE*), temperate zones by an ecozone classification (*KGPTEMP*), and distance from the equator (*EQDIST)* all appear to be important variables. Column (3) adds a proxy for the quality of internal transport infrastructure, the percentage of roads that are paved (*PAVED*). Column (4) adds the logarithms of initial income and population, and also shows that export concentration is particularly associated with fuel exports.

We present the OLS results for a small set of models for *EXCON* in Table 5, repeating our caution about selection bias. The model with the highest posterior probability is reported in column (3). As shown in column (1), three variables alone (*FRTRADE, KGPTEMP, DISTCR*) explain 44% of the variation in *EXCON.* Note that the relationship between *EXCON* and the natural openness measure *FRTRADE* is positive: countries that are predisposed to openness are more likely to have concentrated exports. This may reflect a tendency for open economies to specialize, but a more plausible explanation is that the partial correlation reflects the effect of country size, an important determinant of the Frankel and Romer (1999) measure of natural openness. For example, small island economies are likely to be classed as naturally open, but are unlikely to export a wide range of goods.

Conditional on *FRTRADE*, a lack of access to the sea—as proxied by *LANDLOCK* and *DISTCR*—raises export concentration. A negative and statistically significant coefficient on *KGPTEMP* indicates that developing countries in the ecologically temperate zones are less likely to have concentrated export structures. In column (3) we add our infrastructure variable *PAVED*, which is negatively signed and significant at the 1% level. Combining these variables, we can explain around three-quarters of the variation in the UNCTAD measure of export concentration. The findings are essentially unchanged by the inclusion of regional dummies and initial income, as in columns (4) and (5), although this increases the standard errors and slightly reduces the point estimates for the effect of *DISTCR*.

Taking the findings of this section as a whole, it is clear that geographic characteristics account for a substantial fraction of the international variation in output volatility. By looking not only at the direct relationship between geography and volatility, but also at intermediate outcomes, we have shown that countries remote from the sea are predisposed to high export concentration and output volatility. The strong effect of coastal access may partly reflect other adverse outcomes associated with primary commodity dependence.

7 The role of institutions

A number of recent papers, including the influential contribution of Acemogu et al. (2001), have argued that institutions are a fundamental determinant of long-run development out-

[17] Note that, since we have no data on *EXCON* for Rwanda and Chad, the empirical work using this variable is restricted to 68 countries rather than 70.

comes. A natural question is whether institutions dominate other explanations, including the roles of geography, trade, human capital and certain government policies. Research by Dollar and Kraay (2003), Easterly and Levine (2003), Glaeser et al. (2004) and Rodrik et al. (2004) has examined this issue in various ways.[18] In the empirical work to date, although geography may affect per capita income by influencing the quality of institutions, the direct effects of geography on income levels appear weaker. We will show that the same result is not true for output volatility: geography clearly matters a great deal, even when conditioning on a range of proxies for institutional quality.

To compare the role of geography with that of institutions, we extend our set of candidate predictors. There is a potential drawback of widening the focus in this way. So far, we have concentrated on predetermined variables that can be given a structural interpretation. When looking at institutions as well as geography, the case that our estimates represent structural relationships is harder to justify, because volatility may be a determinant of institutional quality (perhaps via the overall level of development). Although formal institutions are likely to evolve only slowly - for empirical evidence on this see Acemoglu et al. (2001) - in the absence of valid instruments it is difficult to establish whether institutions promote stability, or stability acts as a precursor to better institutions. In this section, we simply treat the institutional measures as exogenous. In the presence of a simultaneity bias in which stability promotes institutional quality, the parameters on institutional variables are likely to be biased away from zero, and the regressions would tend to overstate the beneficial effect of institutions on volatility. Given that favourable geography is often thought to be positively correlated with institutional quality, our estimates would then provide an approximate upper bound on the effects of institutions and a lower bound on those of geography.

We start by looking at the full sample of 88 countries (developing and developed) and initially consider five different measures of institutions: an aggregate governance index (*KKZ*), the Henisz (2000) political constraints index (*PCI*), a second measure of the extent of constraints on the executive (*EXEC*), the competitiveness of political participation (*COMP*), and the type of government, autocratic or democratic (*GTYPE*). The results are shown in column (1) of Table 6. Consistent with the findings of Acemoglu et al. (2003), we find strong evidence that institutional measures should be included in a model of output volatility. The *KKZ* index of governance has a posterior probability of inclusion of 0.99. Scanning across the columns of Table 6, it is clear that even where a particular institutional measure like *KKZ* starts to look fragile, it is substituted by the increased importance of another (consider the posterior probability of inclusion of *EXEC*, a measure of constraints on the executive, in columns 4 and 5).

Even when conditioning on institutional variables, geographical characteristics continue to play an important role in explaining volatility. We continue to find effects of *LAND*-

[18] Rodrik et al. (2004) emphasize the primacy of institutions over geography and international trade. In related work, Easterly and Levine (2003) argue that once institutions are controlled for, policies do not influence long-term income levels.

LOCK, SOILSUIT, and either *POP100CR* or *DISTCR* and *DISTCR2*. Looking at the results in more detail, column (2) restricts attention to the developing country sample, something that does not modify our main conclusions. Similarly, the importance of geography and institutions remains intact when we drop initial income and initial population, as in column (3). In columns (4) and (5) we consider the subset of developing countries for which settler mortality data are available, and include the natural logarithm of settler mortality (*SETMORT*) as an explanatory variable. We find weak evidence that it has an effect on volatility even conditional on institutional measures, with a posterior probability of inclusion of 0.36. This could reflect the imperfections of the proxies for institutional quality, or a correlation between settler mortality and omitted characteristics such as present-day disease burdens.

Table 7 shows the structure of the ten models with the highest posterior model probabilities. Note that even the "best" model receives just 3% of the total posterior probability. This reveals considerable model uncertainty, reinforcing the case for Bayesian methods. The varying structure of these models reveals how alternative measures of institutions substitute for one another in different specifications, reflecting the high correlations between different proxies for institutional quality.

In Table 8 we present OLS estimates of a small set of models for the sample of 70 developing countries. The effects may seem strong, but our usual caution about selection bias applies. The alternative specifications reveal the effects of institutions, but also the continued importance of geography, especially coastal access. The effects of access to the sea remain robust even if we replace the *POP100CR* variable with the linear and square terms of *DISTCR* (column 4) or with the land-based measure *LND100CR* (column 5). As column (4) shows, coastal distance has a non-linear effect on volatility, as suggested by a negative coefficient on the linear term (*DISTCR*) and a positive coefficient on the square term (*DISTCR2)*, indicating a U-shaped relationship. Conditional on whether or not a country is landlocked, volatility increases with distance from the sea for the majority of countries, because only 16 of the 70 countries in our sample are below the turning point implicit in our estimated quadratic. Overall the effects we emphasize are robust to including regional dummies, as in column (6).

8 Robustness

In this section we briefly consider robustness, first to the use of a class of nonlinear models, and secondly to the inclusion of additional (endogenous) explanatory variables. These include measures of policy variability and financial depth suggested by some of the work reviewed in section 2 of the paper, such as Gavin and Hausmann (1997) and Easterly et al. (2001).

The dependent variables in our regressions, either export concentration or the standard deviation of annual growth rates, are non-negative by construction. In this section, we revisit the regression results of Tables 3, 5 and 8 and explore whether a nonlinear transformation of the dependent variable might be appropriate, using the Box-Cox transformation:

$$\begin{aligned} y^{(\lambda)} &= \frac{y^{\lambda}-1}{\lambda}\,,\, \lambda \neq 0 \\ &= \log y \,,\, \lambda = 0 \end{aligned}$$

where y is the original dependent variable. Assuming that the normal linear model applies to the transformed dependent variable, we can estimate the parameters, including λ, by maximum likelihood. We can also test specific transformations using likelihood ratio tests. For the regression models of volatility in Tables 3 and 8, maximum likelihood estimates reject the original scale of the dependent variable (which corresponds to $\lambda = 1$) but do not reject the log transformation ($\lambda = 0$). When we re-estimate the models in Tables 3 and 8 using the natural logarithm of *VOL* as the dependent variable, our findings are essentially unchanged, although the effects of the institution variables in Table 8, especially *KKZ*, are slightly weakened.

For the regression models in Table 5, in which the dependent variable is export concentration, both the original scale and the log transformation are rejected by likelihood ratio tests. A likelihood ratio test typically does not reject $\lambda = 0.5$ and so we have considered estimates of the Table 5 models in which the square root of the export concentration measure is used as the dependent variable. This weakens the effect of *DISTCR* when regional dummies and the fuel-export dummy are also included in the regression, but even then it remains significant at the 20% level; the regional dummies are all insignificant, and deletion of them restores *DISTCR* to significance at the 1% level. In other respects, the results are similar to those presented earlier.

As we documented in section 2, much previous work on volatility has emphasized the roles of macroeconomic policy and financial development. We briefly consider these issues using results contained in Appendix Tables A2 and A3. Appendix Table A2 shows that the volatility of inflation, and of capital flows relative to GDP, both have high posterior probabilities of inclusion. The effects of volatility in fiscal policy and in the real exchange rate are weaker. Since all these variables are likely to be endogenous, we do not emphasize them further, but note that the geographic effects are robust to their inclusion.[19]

In Table A3 using finance indicators, the evidence for a role for coastal access and institutions is noticeably weaker than before; but note that the sample is now reduced to 59 countries, for reasons of data availability. In column (2) volatility is lower for countries with a high ratio of private credit to GDP (the variable we call *PRIV*) while the two have a nonlinear relationship in column (3). This evidence for nonlinearity is consistent with that in Easterly et al. (2001). Again, given the likely endogeneity of financial depth, we do not pursue this analysis in more detail.

[19] A more complete analysis of policy and volatility would examine whether terms-of-trade shocks are amplified by rigid exchange rates: see Broda (2004) and Edwards and Yeyati (2003) for evidence on this point.

9 Conclusions

This paper has sought to explain differences in output volatility across developing countries. Unlike much previous research in this area, we focus on predetermined or slowly changing variables that are more easily given a structural interpretation. Since the number of candidate explanatory variables is large and theories about volatility are not mutually exclusive, we use Bayesian methods to highlight explanatory variables that are robust across a wide range of specifications. The paper follows Fernandez et al. (2002) and Sala-i-Martin et al. (2004) in demonstrating that Bayesian methods can help to improve the rigour of cross-country empirical work.

The main focus of the paper is on the roles of institutions and geography. As might be expected, our work suggests that countries with weak institutions are more volatile. Yet even when conditioning on institutions, we also find effects of geographical characteristics on volatility that past research has typically ignored. We do not simply draw attention to reduced-form correlations, but also look for evidence consistent with a causal interpretation. One of our strongest results is that countries remote from the sea are more volatile. Remoteness is associated with a lack of export diversification, and this in turn yields high volatility in the terms of trade and in output. This result is not sensitive to the precise regression specification, nor is it driven by the contrasting geographies of low income and high income countries.

None of this is to imply that geography is always destiny. We began this paper with an extreme example of adverse geography and primary commodity dependence, Uganda. Tumusiime-Mutebile, in commenting on Collier (2003), notes that since 1999 Uganda has adjusted to sharp declines in the world price of coffee, its main export, and continued to grow rapidly. He attributes successful adjustment to improved fiscal policy and economic reforms that have increased the flexibility of the domestic economy. This hints that the adverse effects of geographic isolation and export concentration can be overcome, and points to a more complex story than we have been able to develop here.

Nevertheless, even quite simple models can explain around two-thirds of the cross-country variation in the standard deviation of annual growth rates. Since we have adopted a Bayesian approach to model uncertainty, these results cannot simply be dismissed as fragile, and the mechanisms and variables we highlight deserve attention in future research on volatility. The paper also contributes to the debate on geography versus institutions as drivers of development outcomes, and provides unusually strong evidence that geography and institutions both matter.

A Appendix 1: Bayesian Model Averaging

In this appendix, we discuss some of the theory behind Bayesian Model Averaging (BMA) and the approaches used to implement BMA in practice. The presentation draws heavily on the clear exposition in Raftery (1995). We also define the sign certainty index that is used in our tables of posterior inclusion probabilities.

A.1 Posterior model probabilities

As section 4 of the paper makes clear, a key step in implementing BMA is the calculation of the posterior model probabilities (PMPs). As before, we use a simple example with just two possible models. The starting point is the expression for a single PMP that is obtained using Bayes' rule:

$$p(M_1 \mid D) = \frac{p(D \mid M_1)p(M_1)}{p(D \mid M_1)p(M_1) + p(D \mid M_2)p(M_2)} \tag{1}$$

Here $p(M_k)$ is the prior probability of model k. A natural benchmark, which we use in our empirical work, is to make the prior assumption that all models are equally likely. This corresponds to an assumption that each predictor enters the model with prior probability one-half, an assumption that we discuss below.

Under this prior, the PMP depends only on terms of the form $p(D \mid M_k)$. This quantity is given by the marginal likelihood:

$$p(D \mid M_k) = \int p(D \mid \theta_k, M_k)p(\theta_k \mid M_k)d\theta_k \tag{2}$$

where $p(\theta_k \mid M_k)$ is the prior distribution over the parameter space associated with model k, and $p(D \mid \theta_k, M_k)$ is the familiar likelihood.

We can now construct a natural measure of the extent to which the data support model 2 relative to model 1. Using the respective versions of (1) for $p(M_1 \mid D)$ and $p(M_2 \mid D)$ implies that:

$$\frac{p(M_2 \mid D)}{p(M_1 \mid D)} = \frac{p(D \mid M_2)}{p(D \mid M_1)} \times \frac{p(M_2)}{p(M_1)}$$

The first term on the right-hand-side is the ratio of marginal likelihoods of the two models, called the Bayes factor for M_2 against M_1. The second term is based on the prior over models, and since we have assumed that the two models are equally likely, this ratio is equal to unity. Then the ratio of posterior model probabilities is equal to the Bayes factor; the equation shows how the posterior probabilities are based on combining the data and priors within models, as reflected in the computed Bayes factor, with the prior over models.

The Bayes factor provides a measure of which model is better supported by the data. The remaining problem is that (2) will usually be a high-dimensional and intractable integral, and therefore difficult to evaluate. Raftery (1995) proposes that a convenient solution is to approximate twice the log Bayes factor using the Bayesian Information Criterion (BIC) due to Schwarz (1978).

For our purposes, the use of BIC has a number of advantages. First, it avoids the need for an explicit specification for the prior distributions $p(\theta_k \mid M_k)$. Second, since we rank models by approximate posterior model probabilities that are based on BIC, our empirical strategy can be interpreted in more conventional terms as a systematic model selection exercise using BIC as the criterion of model adequacy. Third, the implicit use of maximum likelihood estimates to approximate the Bayesian posterior distributions (as in Sala-i-Martin et al. 2004) means that we can move easily between the BMA results and OLS results for specific models. These considerations imply that those who are resistant to Bayesian principles should still find some of our empirical results of interest.

For the special case of a linear regression with normal errors, choosing the model with the lowest BIC corresponds to minimizing:

$$BIC'_k = n\log(1-R_k^2) + q_k \log n$$

where n is the number of observations, R_k^2 is the coefficent of determination for model k, and q_k is the number of slope coefficients for model k. Hence, the model comparisons tend to favour models with a relatively high R^2 but also penalize models that have a large number of parameters. The trade-off between these two considerations is a function of the sample size. The appeal of this criterion is that the weights are not simply arbitrary, as would be the case with a more ad hoc procedure, but are those implied by Bayesian principles combined with specific, but relatively uninformative, prior distributions over parameters.[20] If we assume that there are K models, all presumed equally likely before examining the data, then $p(M_j) = 1/K$ for all j. Using the BIC approximation and the obvious generalization of (1) the PMPs can easily be calculated as:

$$p(M_k \mid D) \approx \frac{\exp(-0.5BIC'_k)}{\sum_{j=1}^{K} \exp(-0.5BIC'_j)}$$

A.2 Prior specifications

We now discuss some of the necessary assumptions in more detail, including our use of the BIC approximation and its relation to specific assumptions about within-model priors, and the specification of prior model probabilities. The use of BIC in model selection is often motivated by asymptotic considerations, as in the original derivation in Schwarz (1978), the textbook derivation of O'Hagan and Forster (2004, p. 180-181) and more general results such as those discussed in Leonard and Hsu (1999, p. 244). Its relevance may go beyond large samples, however. In the context of model selection for linear regressions with known error variance, an important contribution by George and Foster (2000) shows that a natural class of priors can be calibrated so that the ordering of models by their posterior probability

[20]This statement needs qualification, in that the choice of prior specification can always be debated. George and Foster (2000) examine promising empirical Bayes approaches to model selection, in which the penalty for extra model parameters is data-dependent.

is identical to a ranking by an information criterion, for any sample size. Certain choices of prior imply that BIC is the relevant criterion.

Fernandez et al. (2001) examine a range of within-model prior specifications for BMA exercises using simulations, including three priors for which twice the log Bayes factor behaves asymptotically like the BIC. The priors are designed to be relatively uninformative, so that given informative data, the final results place relatively little weight on subjective prior knowledge. For samples of the size considered here, Fernandez et al. (2001) find that priors which could justify use of the BIC approximation perform quite well in a variety of simulations, although may sometimes be inferior to an alternative choice based on the Risk Inflation Criterion introduced in Foster and George (1994) and discussed in George and Foster (2000).

Another important consideration is the prior distribution over the space of models. Here we follow most existing applications of BMA in assuming that all possible models have equal prior probability. This is true of the applications in Brock and Durlauf (2001), Fernandez et al. (2002) and the references given in Fernandez et al. (2001, p. 393). The assumption is a natural starting point, but not innocuous. It corresponds to assuming that each candidate predictor has a zero coefficient with probability one-half, and in principle this could concentrate the prior away from the true model, especially when the true model is parsimonious and the number of possible predictors is large. Sala-i-Martin et al. (2004) point out that in their application, with 67 candidate predictors, most of the prior mass is concentrated on models with 25 or more included variables. This is a less serious issue for our study, since we have a much smaller number of candidate predictors. Even with 25 candidate predictors, 50% of the prior mass is assigned to models with twelve regressors or fewer.

Another problem with the assumption of equal prior model probabilities is that two empirical proxies for the same underlying determinant, such as coastal access, are being assigned the same joint probability of inclusion as two very different determinants. See Brock et al. (2003, p. 285) for more discussion and a possible solution, but implementation in a context such as the present one is not straightforward.

We now discuss the computational aspects of BMA in more detail. A key problem in implementing BMA is the sheer range of possible models. For example, with 30 candidate predictors, there are more than a thousand million possible models (2^{30} to be precise). Thus, most applications of BMA to sizeable data sets do not average over all possible models, but use a search algorithm to identify the subset of models with greatest relevance. To establish this subset, we use the Occam's Window technique described in Madigan and Raftery (1994) and Raftery et al. (1997).

There are two basic variants on this procedure. The first is to exclude from the averaging procedure any model that is much less likely than the model with the highest posterior model probability. For example, all models that have a PMP lower than 1/20 that of the leading model could be excluded. A second approach, used in addition to the first, is to exclude models that have a more likely sub-model nested within them. When the first criterion is used, this is called the "symmetric" Occam's Window. When both criteria are applied, we have the "strict" version of the technique. Either variant tends to reduce massively the number of models used in the averaging process, but does not in itself solve the problem of identifying the models that are likely to lie within Occam's Window. In the case of linear regression, however, the leaps and bounds algorithm of Furnival and Wilson (1974) can be used to identify quickly a set of leading models. One of the variants of Occam's Window can then be applied to this subset. By focusing on only well-fitting models and calculating PMPs based on this subset, the approach treats the worst-fitting models as effectively having a posterior probability of zero.

To implement this procedure, we use the `bicreg` software written for the S-Plus statistical language by Adrian Raftery and revised by Chris Volinsky. This software establishes Occam's Window based on the BIC approximation to the Bayes factors. An alternative would be to use the Markov chain Monte Carlo approach to model uncertainty developed by Madigan and York (1995). These methods are computationally intensive, however. We do not pursue this approach here, but note that the Occam's Window and MCMC approaches give rise to broadly similar results in the empirical application reported in Raftery *et al.* (1997, p. 184).

As with most approaches to empirical research, it would be a mistake to apply and interpret these techniques mechanically. For example, none of the models included in the BMA may be a good approximation to the process that generated the data. Brock et al. (2003, p. 270) and O'Hagan and Forster (2004, p. 166-167) discuss this problem in more detail. It should be noted that no empirical strategy in economics will be immune to this criticism. Given the systematic approach we adopt, we are more likely to identify good approximations than the ad hoc strategies often used in the cross-country literature. Moreover, even if the true model is absent from the set considered, comparisons of the relative posterior probabilities of different models should still be informative, providing some evidence against wide classes of models.

Another problem of interpretation arises where several variables are highly correlated, since the individual posterior probabilities that their effects are non-zero may all be low. Nevertheless, if we sum the PMPs for all models that include at least one of these variables, there may be much stronger evidence that at least one of the variables should be included in the model. This point is closely related to a well-known criticism of Leamer's extreme bounds analysis; see Temple (2000) for discussion and references.

A.3 The sign certainty index

The numbers we report in the BMA tables are posterior probabilities of inclusion, namely the sum of the posterior model probabilities (PMPs) across all the models in which a given coefficient is non-zero. We use a similar method to indicate the probable sign of a relationship. To do this, we sum up the PMPs for all models in which a coefficient is strictly positive (>0), and compare this with the sum of the PMPs for all models in which a coefficient is strictly negative (<0). If the difference between these two totals is less than a threshold we set at 0.20, or the total posterior probability of inclusion is less than 0.20, we do not classify the sign of the relationship. Otherwise, we assign the relationship a sign (+/-). These calculations are performed using modifications of the original `bicreg` code, the details of which are available from the authors.

An alternative and more common approach to a sign certainty index is based on the location of the posterior distribution for a given variable conditional on inclusion. High figures for such an index have to be interpreted carefully. At first glance they can indicate a high degree of certainty about the sign of a relationship even when a variable is present only in a set of models that have low total posterior probability, and hence where the evidence is weak that a variable plays a role in any direction.

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FIGURE 1: TROPICAL LOCATION AND VOLATILITY

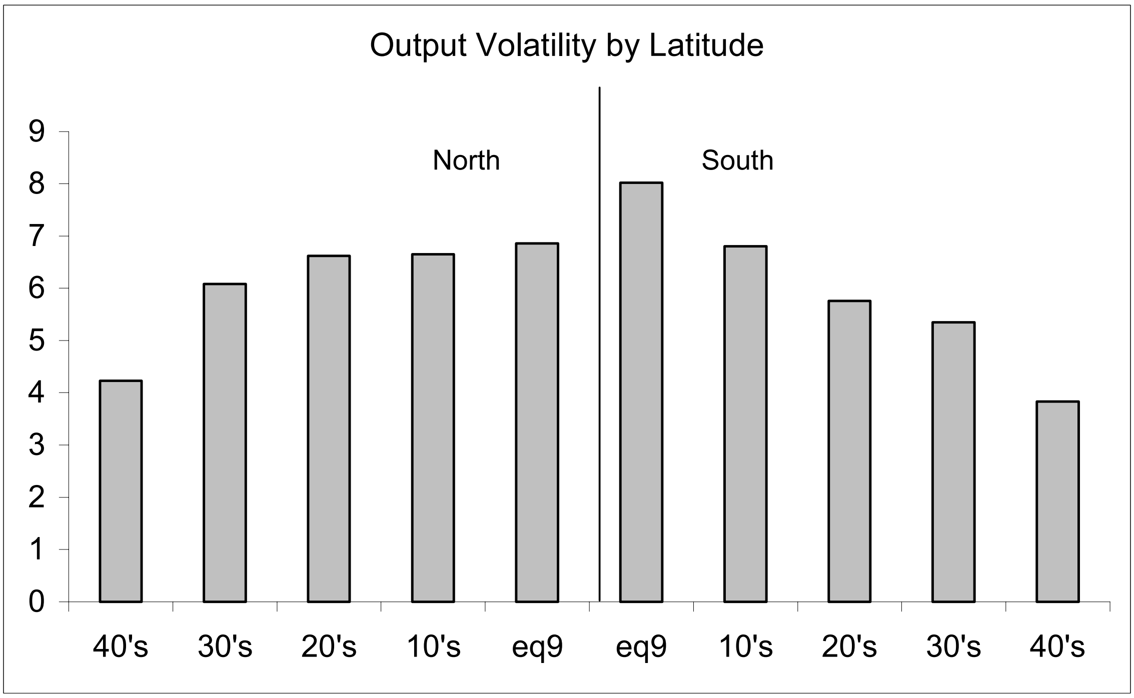
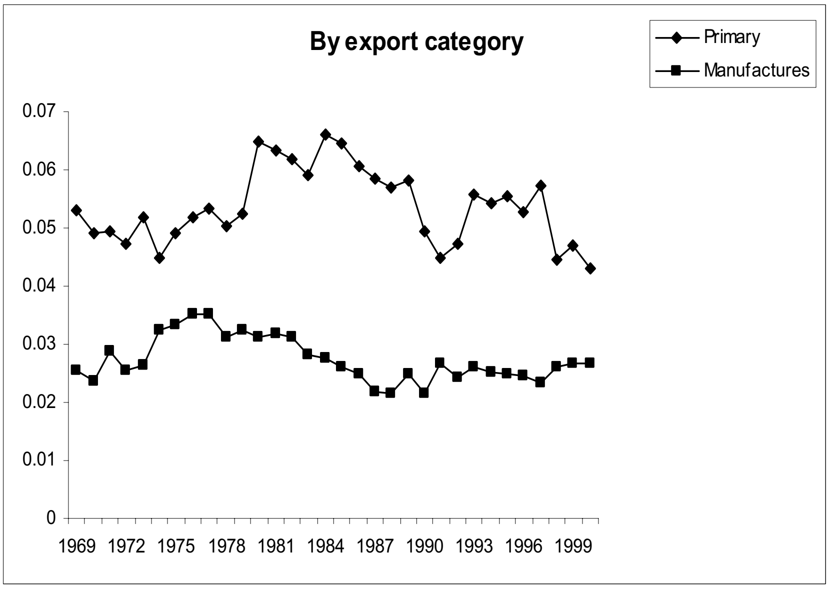


FIGURE 2: EVOLUTION OF OUTPUT VOLATILITY



Notes: Volatility is defined as the standard deviation of annual growth of real GDP per capita. The figure plotted at date T is the median for each group of a ten-year rolling standard deviation based on years T-9 to T. *Primary* and *Manufactures* refers to non-fuel primary commodity and manufactured goods exporters, respectively, based on World Bank classifications.

FIGURE 3: EXPORT CONCENTRATION AND TERMS OF TRADE VOLATILITY

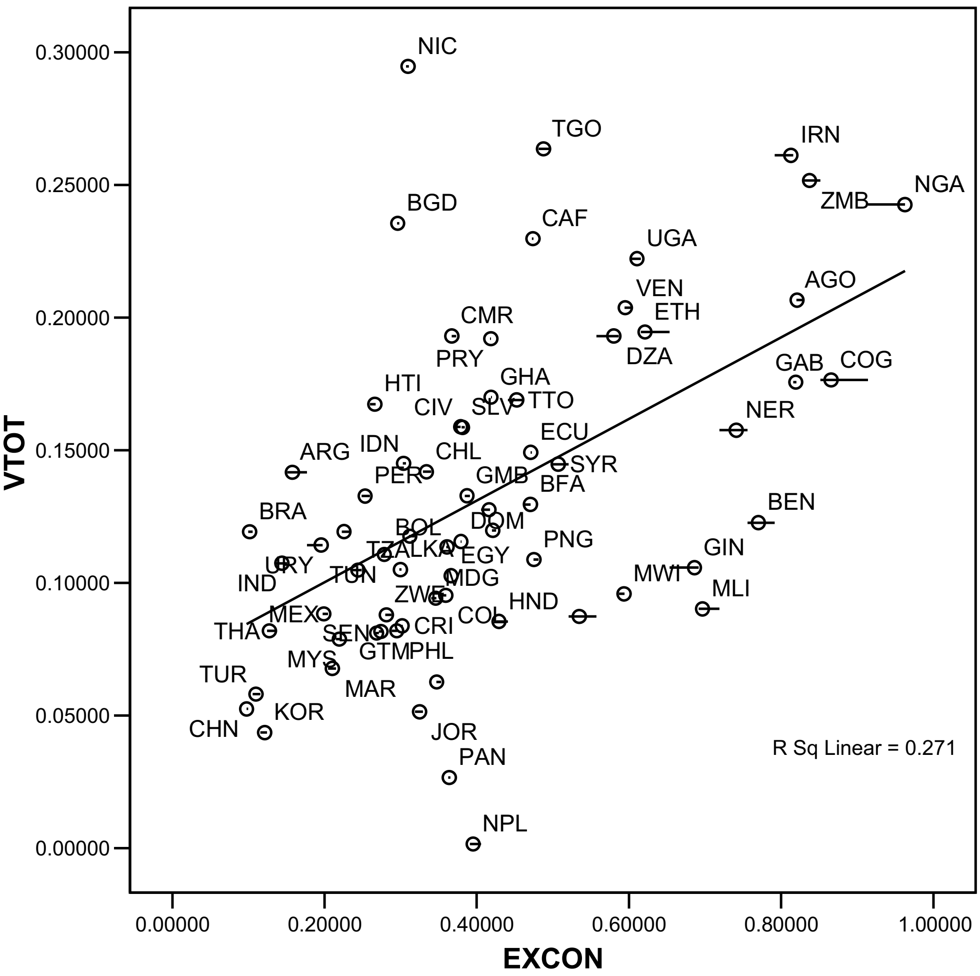


TABLE 1: SOURCES OF OUTPUT VOLATILITY

		Dependent Variable: VOL – Output Volatility									
Sample		*Developing*		*Developing*		*Developing*		*Developing*		*Full Sample*	
Countries		*70*		*70*		*70*		*70*		*88*	
		(1)		*(2)*		*(3)*		*(4)*		*(5)*	
1	*POP60*	0.969	(-)	1.000	(-)	0.982	(-)			0.975	(-)
2	*DISTCR2*	0.969	(+)	0.668	(+)	0.671	(+)	0.177		0.096	
3	*SOILSUIT*	0.913	(-)	0.591	(-)	0.952	(-)	0.978	(-)	0.969	(-)
4	*LANDLOCK*	0.911	(-)	0.992	(-)	0.975	(-)	0.499	(-)	0.909	(-)
5	*DISTCR*	0.467	(-)	0.662	(-)	0.264	(-)	0.064		0.096	
6	*RELIGION*	0.365	(+)	0.188		0.056		0.074		0.065	
7	Initial income, 1960	0.364	(-)	0.674	(-)	0.885	(-)			1.000	(-)
8	South Asia	0.205	(-)	0.169		0.557	(-)	0.835	(-)	0.972	(-)
9	Sub-Saharan Africa	0.098		0.101		0.019		0.247	(+)	0.042	
10	*ZDRYTEMP*	0.043		0.000		0.015		0.343	(-)	0.000	
11	*TROPICAL*	0.042		0.006		0.000		0.069		0.000	
12	*FRTRADE*	0.031		0.000		0.018		0.975	(+)	0.072	
13	*POP100CR*	0.026		0.138		0.464	(-)	0.843	(-)	0.957	(-)
14	*EQDIST*	0.013		0.000		0.000		0.013		0.000	
15	East Asia and Pacific	0.007		0.000		0.000		0.000		0.000	
16	*ZTROPICS*	0.005		0.009		0.051		0.044		0.081	
17	*ETHNIC*	0.005		0.373	(-)	0.168		0.040		0.045	
18	Middle-East & N. Africa	0.000		0.000		0.000		0.011		0.027	
19	Latin America &Caribbean	0.000		0.000		0.000		0.046		0.055	
20	*CMAP3*	0.000		0.000		0.015		0.015		0.140	
21	War Dummy			0.424	(-)	0.398	(-)	0.149		0.164	
22	*ETHNIC*War*			0.845	(+)	0.537	(+)	0.298	(+)	0.488	(+)
23	*VTOT*					1.000	(+)	1.000	(+)	1.000	(+)

Notes

The dependent variable, *VOL,* is defined as the standard deviation of annual growth of real GDP per capita during the period 1960-1999. The *Full Sample* (last column) includes 18 high-income OECD countries as well as 70 developing countries. See Appendix 2 for a description of variables.

The numbers reported in the table are the posterior inclusion probabilities for each variable: in other words, the sum of posterior model probabilities over all models in which the variable is included. We also report an indicator of the direction of the relationship, based on the sum of posterior model probabilities over all models in which a variable acts in a given direction (say, positive). Where no sign is given, this indicates that the sign of the estimated relationship is uncertain. The precise assignment rule is described in Appendix 1.

TABLE 2: TOP TEN MODELS AND THEIR POSTERIOR PROBABILITIES

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Initial Income	•	•	•	•	•	•		•	•	•
POP60	•	•	•	•	•	•	•	•	•	•
POP100CR	•	•							•	
LANDLOCK	•	•	•	•	•	•	•	•	•	•
DISTCR2			•	•	•	•	•	•		•
SOILSUIT	•	•	•	•	•	•	•	•	•	
WAR			•			•	•		•	•
EWAR		•	•			•	•	•	•	•
VTOT	•	•	•	•	•	•	•	•	•	•
South Asia	•	•		•		•		•	•	
DISTCR										•
ETHNIC										•
PMP	*0.081*	*0.052*	*0.050*	*0.042*	*0.036*	*0.031*	*0.027*	*0.023*	*0.022*	*0.022*

Notes:
This table shows the ten best models, ranked by their posterior model probability (PMP). The underlying sample consists of 70 developing countries. See the appendix for variable description. Note that all the top ten models contain a measure of coastal access, either POP100CR or DISTCR2.

TABLE 3: GEOGRAPHY AND OUTPUT VOLATILITY

Dependent Variable: VOL – Output Volatility								
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Constant	.214	.250	.188	.226	.202	.199	.232	.231
	(5.79)	(6.53)	(5.31)	(5.83)	(4.82)	(3.67)	(4.12)	(3.81)
Initial Income	-.007	-.009	-.007	-.009	-.010	-.010	-.010	-.010
	(1.73)	(2.17)	(2.08)	(2.55)	(2.41)	(1.82)	(1.83)	(1.74)
POP60	-.008	-.009	-.007	-.008	-.011	-.009	-.008	-.008
	(4.97)	(5.81)	(4.22)	(5.05)	(5.24)	(3.35)	(3.39)	(3.22)
SOILSUIT	-.094	-.106	-.103	-.116	-.078	-.086	-.097	-.100
	(2.26)	(2.57)	(2.71)	(2.95)	(1.94)	(2.02)	(2.32)	(2.31)
POP100CR	-.028	-.041	-.024	-.038			-.036	
	(3.25)	(4.01)	(2.90)	(3.82)			(3.24)	
LND100CR								-.031
								(2.79)
DISTCR2					.129	.111		
					(4.00)	(2.66)		
LANDLOCK		-.020		-.022	-.028	-.025	-.025	-.021
		(2.23)		(2.46)	(3.42)	(2.60)	(2.89)	(2.47)
VTOT			.154	.160	.124	.121	.138	.137
			(3.53)	(4.10)	(2.88)	(2.73)	(3.15)	(3.15)
War dummy					-.046	-.040	-.030	-.037
					(2.47)	(2.12)	(1.38)	(1.76)
ETHNIC					-.018	-.019	-.026	-.020
					(1.18)	(1.12)	(1.59)	(1.25)
*ETHNIC**War					.086	.077	.065	.073
					(2.44)	(2.19)	(1.68)	(1.99)
L. A. & Caribbean						-.002	-.001	-.001
						(0.35)	(0.14)	(0.07)
East Asia & Pacific						-.003	.001	.0003
						(0.60)	(0.12)	(0.03)
South Asia						-.016	-.017	-.015
						(1.38)	(1.61)	(1.16)
M. East & N. Africa						-.001	.005	.001
						(0.05)	(0.42)	(0.06)
Sub-Saharan Africa						.002	.009	.008
						(0.21)	(0.88)	(0.58)
Std coefficients (β's)								
POP60	-0.43	-0.50	-0.39	-0.45	-0.58	-0.49	-0.41	-0.45
SOILSUIT	-0.27	-0.30	-0.29	-0.33	-0.22	-0.25	-0.27	-0.29
POP100CR	-0.37	-0.55	-0.32	-0.51			-0.48	
DISTCR2					0.56	0.48		
VTOT			0.36	0.37	0.29	0.28	0.32	0.32
R^2	*0.34*	*0.40*	*0.46*	*0.53*	*0.61*	*0.63*	*0.64*	*0.61*
100σ	*2.22*	*2.15*	*2.02*	*1.91*	*1.78*	*1.82*	*1.79*	*1.85*
N	*70*	*70*	*70*	*70*	*70*	*70*	*70*	*70*

Notes
The dependent variable is *VOL*, output volatility. The sample consists of 70 developing countries. Numbers reported in parentheses are absolute t-statistics computed from MacKinnon-White (1985) heteroskedasticity-robust standard errors. Standardized coefficients (betas) show the effect of a one standard deviation change in the variable, in terms of standard deviations of the dependent variable; they are not shown for GDP per capita, binary variables or where interactions are present. See the appendices for a full variable description.

TABLE 4: MODELS FOR EXPORT CONCENTRATION INDEX

Sample		*Developing*		*Developing*		*Developing*		*Developing*	
Countries		*68*		*68*		*68*		*68*	
Variable		*(1)*		*(2)*		*(3)*		*(4)*	
1	*FRTRADE*	0.989	(+)	0.990	(+)	1.000	(+)	0.949	(+)
2	*DISTCR2*	0.886	(+)	0.893	(+)	0.919	(+)	0.332	(+)
3	*KGPTEMP*	0.680	(-)	0.698	(-)	0.672	(-)	0.552	(-)
4	*EQDIST*	0.251	(-)	0.239	(-)	0.243	(-)	0.070	
5	*DISTCR*	0.182		0.167		0.119		0.662	(+)
6	Agriculture share in GDP			0.144		0.192		0.129	
7	South Asia	0.119		0.107		0.056		0.000	
8	*SOILSUIT*	0.116		0.111		0.072		0.000	
9	Sub-Saharan Africa	0.093		0.082		0.063		0.068	
10	*TPVOL*	0.058		0.045		0.030		0.023	
11	*TROPPOP*	0.060		0.057		0.043		0.027	
12	*POP100KM*	0.035		0.033		0.000		0.066	
13	*TROPICAL*	0.033		0.031		0.024		0.023	
14	*POP100CR*	0.041		0.030		0.008		0.029	
15	East Asia and Pacific	0.014		0.014		0.000		0.017	
16	Middle East & N.Africa	0.022		0.010		0.048		0.036	
17	*ETHNIC*	0.011		0.010		0.000		0.000	
18	Latin America &Caribbean	0.000		0.000		0.008		0.126	
19	*LANDLOCK*	0.000		0.000		0.000		0.766	(+)
20	*CMAP3*	0.031		0.012		0.000		0.000	
21	Distance to major markets	0.000		0.000		0.000		0.007	
22	*KGPTRSTR*	0.000		0.000		0.000		0.006	
23	*PAVED*					0.252	(-)	0.925	(-)
24	War Dummy					0.042		0.000	
25	*ETHNIC**War					0.190		0.000	
26	Fuel exporting							1.000	(+)
27	Manufactures exporting							0.000	
27	Primary exporting							0.005	
29	*POP60*							0.067	
30	Initial income, 1960							0.000	

Notes

The dependent variable is *EXCON*, the UNCTAD export concentration index described in the main text. High values correspond to a lack of export diversification. The sample is 68 developing countries. The numbers reported in the table are the posterior inclusion probabilities for each variable (the sum of posterior model probabilities over all models in which the variable is included). We also report an indicator of the direction of the relationship; see Table 1 for additional notes.

TABLE 5: DETERMINANTS OF EXPORT CONCENTRATION

Dependent Variable: EXCON - Export Concentration Index					
	(1)	(2)	(3)	(4)	(5)
Constant	-.407	-.280	-.227	-.231	-.344
	(2.90)	(2.08)	(1.86)	(0.20)	(0.37)
FRTRADE	.136	.119	.127	.109	.110
	(4.23)	(4.66)	(5.42)	(3.54)	(3.42)
KGPTEMP	-.259	-.204	-.129	-.106	-.114
	(4.38)	(4.06)	(2.23)	(1.44)	(1.54)
DISTCR	.093	.065	.060	.041	.042
	(5.16)	(3.35)	(3.36)	(1.89)	(1.90)
LANDLOCK		.112	.100	.109	.111
		(2.02)	(1.87)	(2.05)	(2.00)
Fuel-exporting dummy		.356	.366	.362	.356
		(6.16)	(6.58)	(6.62)	(5.96)
PAVED			-.188	-.237	-.239
			(2.91)	(2.63)	(2.63)
Sub-Saharan Africa				.182	.188
				(0.16)	(0.21)
East Asia & Pacific				.178	.184
				(0.16)	(0.21)
Latin America & Caribbean				.123	.117
				(0.11)	(0.13)
South Asia				.134	.143
				(0.12)	(0.16)
Middle East & North Africa				.215	.220
				(0.19)	(0.25)
Initial Income, 1960					.014
					(0.44)
Std coefficients (β's)					
FRTRADE	0.43	0.37	0.40	0.34	0.34
KGPTEMP	-0.32	-0.25	-0.16	-0.13	-0.14
DISTCR	0.50	0.35	0.32	0.22	0.22
PAVED			-0.21	-0.26	-0.27
R^2	0.43	0.71	0.74	0.77	0.77
σ	0.16	0.11	0.11	0.11	0.11
N	68	68	68	68	68

The dependent variable is *EXCON*, the UNCTAD export concentration index described in the main text. High values correspond to a lack of export diversification. The sample is 68 developing countries. Numbers reported in parentheses are absolute t-statistics computed from MacKinnon-White (1985) heteroskedasticity-robust standard errors. Standardized coefficients (betas) show the effect of a one standard deviation change in the variable, in terms of standard deviations of the dependent variable; they are not shown for GDP per capita or binary variables. See the appendices for a full variable description.

TABLE 6: INSTITUTIONS AND GEOGRAPHY COMBINED

		Dependent Variable: VOL – Output Volatility									
Sample		*Full Sample*		*Developing*		*Developing*		*Settler Mortality*		*Settler Mortality*	
Countries		*88*		*70*		*70*		*57*		*57*	
Variable		*(1)*		*(2)*		*(3)*		*(4)*		*(5)*	
1	*SOILSUIT*	1.000	(-)	0.853	(-)	1.000	(-)	0.878	(-)	0.915	(-)
2	*KKZ*	0.990	(-)	0.879	(-)	0.987	(-)	0.032		0.014	
3	*POP60*	0.971	(-)	0.927	(-)	-	-	1.000	(-)	1.000	(-)
4	*ETHNIC*War*	0.852	(+)	0.677	(+)	0467	(+)	0.065		0.149	
5	War Dummy	0.841	(-)	0.665	(-)	0.376	(-)	0.044		0.108	
6	*RELIGION*	0.775	(+)	0.242	(+)	0.259	(+)	0.031		0.011	
7	*VTOT*	0.743	(+)	0.722	(+)	0.819	(+)	1.000	(+)	1.000	(+)
8	*LANDLOCK*	0.589	(-)	0.850	(-)	0.326	(-)	1.000	(-)	1.000	(-)
9	*POP100CR*	0.519	(-)	0.667	(-)	0.942	(-)	0.000		0.000	
10	*CMAP3*	0.509	(+)	0.006		0.016		0.012		0.009	
11	South Asia	0.465	(-)	0.300	(-)	0.994	(-)	0.665	(-)	0.597	(-)
12	*PCI*	0.371	(-)	0.324	(-)	0.069		0.130		0.153	
13	*ETHNIC*	0.293	(-)	0.364	(-)	0.033		0.531	(-)	0.504	(-)
14	*DISTCR*	0.148		0.451	(-)	0.055		1.000	(-)	0.982	(-)
15	*GTYPE*	0.148		0.315	(-)	0.014		0.086		0.058	
16	*DISTCR2*	0.142		0.579	(+)	0.092		1.000	(+)	1.000	(+)
17	Middle East & N. Africa	0.068		0.000		0.000		0.000		0.005	
18	*ZTROPICS*	0.036		0.000		0.013		0.025		0.000	
19	*FRTRADE*	0.035		0.073		1.000	(+)	1.000	(-)	0.968	(-)
20	*COMP*	0.022		0.037		0.055		0.052		0.019	
21	Initial income, 1960	0.005		0.111		-	-	0.983	(-)	0.905	(-)
22	Sub-Saharan Africa	0.004		0.011		0.031		0.446	(+)	0.334	(+)
23	W. Europe & N. America	0.004		-	-	-	-	-	-	-	-
24	*EXEC*	0.004		0.008		0.029		0.919	(-)	0.841	(-)
25	*TROPICAL*	0.000		0.004		0.000		0.062		0.065	
26	*ZDRYTEMP*	0.000		0.013		0.204	(-)	0.000		0.000	
27	East Asia and Pacific	0.000		0.000		0.000		0.023		0.000	
28	Latin America &Caribbean	0.000		0.004		0.000		0.000		0.000	
29	*SETMORT*	-	-	-	-	-	-	-	-	0.359	(+)

Notes
The dependent variable is output volatility, *VOL,* over 1960-1999. The *Full Sample* includes 18 high-income OECD countries as well as 70 developing countries. The *Settler Mortality Sample* consists of 57 developing countries for which colonial settler mortality data are available. See the appendices for a full variable description. The numbers reported in the table are the posterior inclusion probabilities for each variable (the sum of posterior model probabilities for all models in which the variable is included). We also report an indicator of the direction of the relationship; see Table 1 for additional notes.

TABLE 7: TOP TEN MODELS AND THEIR POSTERIOR PROBABILITIES

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
POP60	•	•	•	•	•	•	•	•	•	•
Initial income		•								
DISTCR	•		•	•	•	•	•			
DISTCR2	•		•		•	•	•		•	
FRTRADE				•						
POP100CR		•		•		•	•	•		•
LANDLOCK	•	•	•		•	•	•	•	•	•
SOILSUIT		•	•	•	•			•	•	•
ETHNIC	•					•	•			
WAR	•		•		•	•	•		•	•
EWAR	•		•		•	•	•		•	•
VTOT		•	•	•				•	•	•
KKZ	•	•	•	•	•	•	•		•	•
PCI							•	•		•
GTYPE	•		•		•	•				
South Asia		•		•						
PMP	*0.027*	*0.025*	*0.024*	*0.022*	*0.021*	*0.020*	*0.020*	*0.019*	*0.019*	*0.018*

Notes:

This table shows the ten best models, ranked by their posterior model probability (PMP). The underlying sample consists of 70 developing countries. See the appendix for variable description. Note that all the top ten models contain a measure of coastal access, at least one of POP100CR or DISTCR2.

TABLE 8: GEOGRAPHY, INSTITUTIONS, AND OUTPUT VOLATILITY

Dependent variable: VOL – Output volatility						
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Constant	.157	.165	.157	.202	.149	.147
	(4.61)	(5.28)	(6.11)	(6.03)	(5.25)	(4.97)
POP60	-.008	-.008	-.008	-.008	-.008	-.007
	(4.07)	(4.18)	(4.53)	(4.82)	(4.30)	(3.16)
POP100CR	-.042	-.040	-.028			-.029
	(4.07)	(3.60)	(3.09)			(2.89)
LANDLOCK	-.018	-.022	-.020	-.026	-.015	-.020
	(2.17)	(2.59)	(2.68)	(3.41)	(2.07)	(2.74)
SOILSUIT	-.124	-.111	-.092	-.059	-.094	-.098
	(3.11)	(2.81)	(2.30)	(1.79)	(2.28)	(2.34)
VTOT	.157	.149	.099	.071	.100	.094
	(3.84)	(3.19)	(2.14)	(1.75)	(2.21)	(2.06)
WAR		-.041	-.050	-.054	-.054	-.042
		(1.94)	(2.69)	(2.88)	(2.56)	(2.34)
ETHNIC		-.009	-.015	-.016	-.010	-.023
		(0.64)	(1.05)	(1.36)	(0.61)	(1.51)
*ETHNIC*WAR*		.078	.089	.094	.094	.079
		(2.17)	(2.94)	(3.08)	(2.82)	(2.72)
KKZ			-.014	-.012	-.014	-.014
			(2.42)	(2.23)	(2.25)	(2.17)
GTYPE			-.102	-.111	-.096	-.050
			(1.91)	(2.19)	(1.78)	(0.72)
DISTCR				-.036		
				(2.73)		
DISTCR2				.004		
				(3.23)		
LND100CR					-.021	
					(2.37)	
Std coefficients (β's)						
POP60	-0.42	-0.45	-0.44	-0.45	-0.45	-0.39
POP100CR	-0.56	-0.53	-0.37			-0.39
SOILSUIT	*-0.35*	-0.31	-0.26	-0.17	-0.27	-0.28
VTOT	0.37	0.35	0.23	0.16	0.23	0.22
KKZ			-0.25	-0.22	-0.24	-0.26
GTYPE			-0.19	-0.21	-0.18	-0.10
LND100CR					-0.28	
Regional dummies	No	No	No	No	No	Yes
R^2	0.48	0.54	0.64	0.67	0.61	0.66
100σ	1.98	1.92	1.73	1.68	1.78	1.75
N	70	70	70	70	70	70

Notes to Table 8:

The dependent variable is output volatility, VOL. Numbers reported in parentheses are absolute t-statistics computed from MacKinnon-White (1985) heteroskedasticity-robust standard errors. Coefficients on regional dummies in column 6 are not reported. Standardized coefficients (betas) show the effect of a one standard deviation change in the variable, in terms of standard deviations of the dependent variable; they are not shown for binary variables or where nonlinearities are present. See the appendices for a full variable description.

Appendix 2:

LIST OF COUNTRIES IN THE FULL SAMPLE, VARIABLE DEFINITIONS, AND SOME DESCRIPTIVE STATISTICS

Latin America & Caribbean

ARG	Argentina
BOL	Bolivia
BRA	Brazil
CHL	Chile
COL	Colombia
CRI	Costa Rica
DOM	Dominican Republic
ECU	Ecuador
GTM	Guatemala
HND	Honduras
HTI	Haiti
MEX	Mexico
NIC	Nicaragua
PAN	Panama
PER	Peru
PRY	Paraguay
SLV	El Salvador
TTO	Trinidad and Tobago
URY	Uruguay
VEN	Venezuela, RB

Sub-Saharan Africa

AGO	Angola
BEN	Benin
BFA	Burkina Faso
CAF	Central African Republic
CIV	Cote d'Ivoire
CMR	Cameroon
COG	Congo, Rep.
ETH	Ethiopia
GAB	Gabon
GHA	Ghana
GIN	Guinea
GMB	Gambia, The
KEN	Kenya
MDG	Madagascar
MLI	Mali
MOZ	Mozambique
MRT	Mauritania
MWI	Malawi
NER	Niger
NGA	Nigeria
RWA	Rwanda
SEN	Senegal
SLE	Sierra Leone
TCD	Chad
TGO	Togo
TZA	Tanzania
UGA	Uganda
ZAF	South Africa
ZMB	Zambia
ZWE	Zimbabwe

East Asia & Pacific

AUS	Australia*
CHN	China
IDN	Indonesia
KOR	Korea, Rep.
MYS	Malaysia
NZL	New Zealand*
PHL	Philippines
PNG	Papua New Guinea
THA	Thailand

South Asia

BGD	Bangladesh
IND	India
LKA	Sri Lanka
NPL	Nepal
PAK	Pakistan

Middle East & North Africa

DZA	Algeria
EGY	Egypt, Arab Rep.
GRC	Greece*
IRN	Iran, Islamic Rep.
JOR	Jordan
MAR	Morocco
POR	Portugal*
SYR	Syrian Arab Rep.
TUN	Tunisia

*W. Europe & North America**

AUT	Austria
CAN	Canada
DNK	Denmark
FIN	Finland
FRA	France
GER	Germany
IRL	Ireland
ITA	Italy
NLD	Netherlands
NOR	Norway
ESP	Spain
SWE	Sweden
CHE	Switzerland
GBR	Great Britain

Other

TUR	Turkey

Note

Countries/regions marked with an asterisk (*) are excluded from the developing country sample.

DESCRIPTION OF MAIN VARIABLES AND THEIR SOURCES

VARIABLE	DESCRIPTION	SOURCE
OUTPUT VOLATILITY		
VOL	Standard deviation of annual growth of real, chain-weighted GDP per capita, 1960-99	Constructed from Penn World Tables, Release 6.1, Heston, Summers and Aten (2002).
TRADE		
VTOT	S.D. of the first log-differences of a terms of trade index for goods and services	GDF & World Development Indicators
EXCON	Export Concentration Index, averaged 1980-2000; see main text for more details.	UNCTAD Handbook of Statistics
FRTRADE	Natural log of the Frankel-Romer measure of predisposition to external trade	Frankel and Romer (1999)
EXPORT CATEGORIES	Dummy for fuel, non-fuel primary, and manufactured good exporting countries	World Bank – GDN Database
TPVOL	S. D. of trading partner's GDP growth per capita growth (% average by trade share)	World Bank – GDN Database
GEOGRAPHY		
KGPTEMP	Proportion of people in the Koeppen-Geigger temperate zone	CID, Harvard University. Gallup *et al*. (1999).
KGPTRSTR	Proportion of people in the Koeppen-Geigger tropical/subtropical zone	CID, Harvard University. Gallup *et al*. (1999).
ZDRYTEMP	Holdridge classification for dry-temperate zones	http://www.cid.harvard.edu
ZTROPICS	Holdridge classification for the tropical zones	http://www.cid.harvard.edu
POP100KM	Proportion of the population in 1994 within 100km of the coastline	Gallup *et al*. (1999).
POP100CR	Proportion of the population in 1994 within 100km of the coastline or ocean-navigable river.	Gallup *et al*. (1999).
LANDLOCK	Dummy for landlocked country, excluding countries in Western and Central Europe	Gallup *et al*. (1999).
TROPICAL	Dummy for tropical countries if the absolute value of latitude is less than or equal to 23	World Bank-Global Development Network database
TROPPOP	Population in the geographical tropics (%)	http://www.cid.harvard.edu
SOILSUIT	Average percentage of each soil type that is moderately suitable for six rain fed crops	FAO Digital Soil Map of the Word, FAO (1995).
EQDIST	Latitude – distance from equator	http://www.cid.harvard.edu
CMAP3	Index of precipitation anomalies based on below average precipitation and drought conditions	Earth Institute, Columbia University
IND2RMS	Root mean square of an index of precipitation anomalies, where the index is defined as the absolute value of standardized monthly precipitation anomalies, weighted according to the seasonal distribution of rainfall	Earth Institute, Columbia University
DISTCR	Log of mean distance to nearest coastline or sea-navigable river (km)	http://www.cid.harvard.edu
DISTCR2	Square of *DISTCR*	http://www.cid.harvard.edu
LND100CR	The proportion of a country's total area within 100km of the ocean or ocean navigable river	Gallup *et al*. (1999).
INSTITUTIONS		
SETMORT	Log of settler mortality ("logem4")	Acemoglu et al (2001)
KKZ	Average of six measures of institutional development institutional: voice and accountability, political stability and absence of	Kaufmann *et al*. (1999)

	violence, government effectiveness, light regulatory burden, rule of law, and freedom from graft	
PCI	Political Constraints Index is a structurally derived measure of the feasibility of policy change (the extent to which a change in the preferences of any one actor may lead to a change in government policy).	Henisz (2001), 2002 release.
EXEC	Average Constraints on the executive	POLITY IV dataset by Robert Gurr
COMP	Competitiveness of political participation is a subjective measure that investigates whether political participation is (a) competitive, (b) transitional, (c) fractional (d) restricted, or (e) suppressed.	POLITY IV by Robert Gurr
GTYPE	Government type, defined as the difference between democracy and autocracy scores.	POLITY IV by Robert Gurr Lodegran (2001)
POLICY		
VREER	S. D. of changes in the real effective exchange rate index (1960-98)	Global Development Finance
Inflation Volatility	S. D. of log of annual inflation rate (1961-99)	World Development Indicators & Global Development Finance
Fiscal Volatility	S. D. of fiscal surplus to GDP ratio (1971-97)	World Development Indicators & Global Development Finance
Volatility of Capital Flows	Coefficient of variation of the ratio of private capital flows to GDP (1975-98)	International Financial Statistics
FINANCE		
PRIV	Credit extended to the private sector by deposit money banks and other financial institutions (as a ratio of GDP)	Beck, Demirguc-Kunt and Levine (1999)
LLY	Ratio of Liquid liabilities to GDP	Beck, Demirguc-Kunt and Levine (1999)
OTHER		
ETHNIC	Ethnic fractionalization index	Alesina et al. (2003)
RELIGION	Index of religious fractionalization	Alesina et al. (2003)
WAR	0/1 indicator for countries that participated in an external war over the period 1960-85	Gallup *et al*. (1999). Original source: Barro (1994).
POP60	Log of total population in 1960	World Development Indicators

SELECTED DESCRIPTIVE STATISTICS

TRADE

	VOL	EXCON	VTOT	FRTRADE	DISTCR	POP100CR	LANDLOCK
VOL	1.0000						
EXCON	0.4831	1.0000					
VTOT	0.4231	0.5204	1.0000				
FRTRADE	0.3053	0.3028	0.0775	1.0000			
DISTCR	0.2696	0.3787	0.1984	-0.2823	1.0000		
POP100CR	-0.3593	-0.3732	-0.1354	0.1751	-0.8693	1.0000	
LANDLOCK	0.1415	0.2939	0.1101	-0.1019	0.4825	-0.5600	1.000

INSTITUTIONS

	VOL	COMP	KKZ	PCI	EXEC	GTYPE
VOL	1.0000					
COMP	-0.4594	1.0000				
KKZ	-0.4879	0.4409	1.0000			
PCI	-0.5041	0.8284	0.4428	1.0000		
EXEC	-0.4357	0.4132	0.3544	0.4180	1.0000	
GTYPE	-0.4772	0.8708	0.4456	0.9341	0.4092	1.0000

GEOGRAPHY

	VOL	TROPICAL	KGPTEMP	POP100CR	LANDLOCK	SOILSUIT	LND100CR
VOL	1.0000						
TROPICAL	0.1731	1.0000					
KGPTEMP	-0.0473	-0.7208	1.0000				
POP100CR	-0.3593	-0.0582	0.1234	1.0000			
LANDLOCK	0.1415	0.1446	-0.2182	-0.5894	1.0000		
SOILSUIT	-0.0687	0.4148	-0.2083	-0.2615	0.0796	1.0000	
LND100CR	-0.3379	0.0572	0.0069	0.9054	-0.4946	-0.2454	1.0000

Appendix 3 – material for working paper version

TABLE A1: MODELS FOR TERMS OF TRADE VOLATILITY

Dependent Variable		*VTOT*		*VTOT*		*VTOT*		*VTOT*		*VTOT*	
Sample		*Developing*		*Developing*		*Developing*		*Developing*		*Developing*	
Countries		*68*		*68*		*68*		*68*		*68*	
Variable		*(1)*		*(2)*		*(3)*		*(4)*		*(5)*	
1	East Asia and Pacific	0.722	(-)	0.722	(-)	0.722	(-)	0.110		0.096	
2	*EQDIST*	0.442	(-)	0.449	(-)	0.449	(-)	0.043		0.000	
3	*DISTCR2*	0.386	(+)	0.387	(+)	0.387	(+)	0.000		0.000	
4	*LND100CR*	0.199		0.200		0.200		0.000		0.021	
5	*CMAP3*	0.145		0.132		0.132		0.076		0.034	
6	*DISTCR*	0.120		0.120		0.120		0.000		0.021	
7	*KGPTEMP*	0.090		0.090		0.089		0.000		0.000	
8	*POP100CR*	0.084		0.077		0.077		0.000		0.000	
9	*KGPSTR*	0.059		0.066		0.066		0.065		0.022	
10	*TROPICAL*	0.058		0.058		0.058		0.016		0.000	
11	*TROPPOP*	0.057		0.057		0.057		0.016		0.000	
12	Sub-Saharan Africa	0.043		0.043		0.043		0.000		0.000	
13	Middle East & N. Africa	0.037		0.030		0.030		0.000		0.007	
14	*TPVOL*	0.021		0.021		0.021		0.079		0.008	
15	*ETHNIC*	0.019		0.019		0.019		0.000		0.000	
16	South Asia	0.011		0.011		0.011		0.000		0.000	
17	*Distance from Major Markets*	0.010		0.010		0.000		0.060		0.026	
18	*FRTRADE*	0.008		0.008		0.008		0.062		0.021	
19	*SOILSUIT*	0.000		0.000		0.000		0.043		0.056	
20	*LANDLOCK*	0.000		0.000		0.000		0.000		0.000	
21	Latin America &Caribbean	0.000		0.000		0.000		0.212	(+)	0.295	(+)
22	Initial income, 1960			0.014		0.014		0.071		0.138	
23	*POP60*			0.000		0.000		0.022		0.000	
24	Agriculture share in GDP					0.010		0.056		0.596	(+)
25	*EXCON*							1.000	(+)	0.594	(+)
26	Dummy for fuel exporters									0.647	(+)
27	Dummy for manufactures exporters									0.118	
28	Dummy for non-fuel primary exporters									0.233	(+)

Notes
See Appendix 2 for a full variable description.

The numbers reported in the table are the posterior inclusion probabilities for each variable (the sum of posterior model probabilities for all models in which the variable is included). We also report an indicator of the direction of the relationship, based on the sum of posterior model probabilities for all models in which a variable acts in a given direction (say, positive). Where no sign is given, the direction of the relationship is judged uncertain. The precise assignment rule is described in the Appendix 1.

TABLE A2: ROBUSTNESS TO MEASURES OF POLICY VOLATILITY

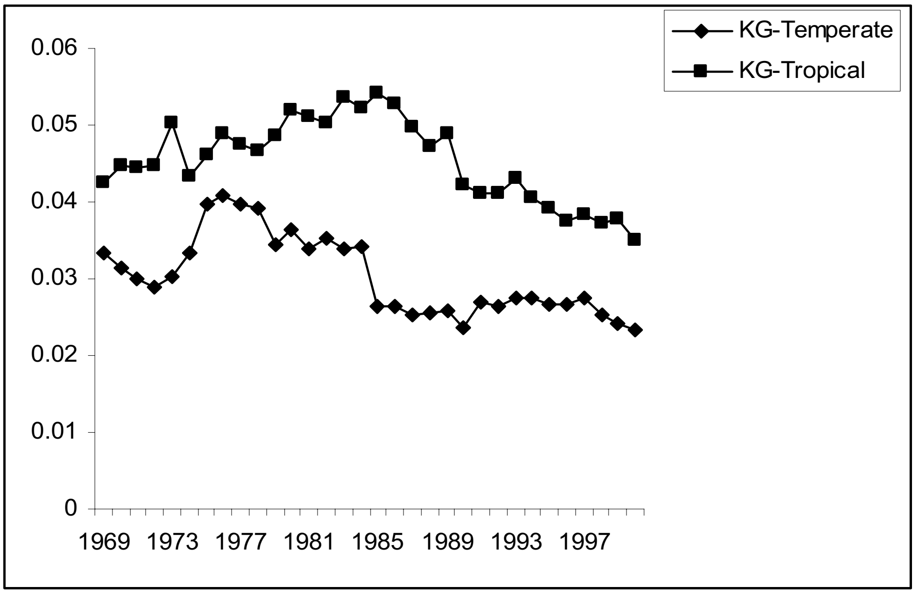
Dependent Variable		*VOL*		*VOL*		*VOL*		*VOL*	
Sample		*Developing*		*Developing*		*Developing*		*Developing*	
Countries									
Variable		*(1)*		*(2)*		*(3)*		*(4)*	
1	*POP60*	0.969	(-)	0.980	(-)	0.706	(-)	1.000	(-)
2	*LANDLOCK*	0..931	(-)	0.992	(-)	0.506	(-)	0.994	(-)
3	*DISTCR2*	0.910	(+)	0.945	(+)	0.622	(+)	0.928	(+)
4	*DISTCR*	0.870	(-)	0.939	(-)	0.543	(-)	0.794	(-)
5	*KKZ*	0.663	(-)	0.985	(-)	0.844	(-)	0.463	(-)
6	*ETHNIC*War*	0.561	(+)	0.859	(+)	0.383	(+)	0.988	(+)
7	*GTYPE*	0.544	(-)	0.485	(-)	0.142		0.894	(-)
8	War Dummy	0.525	(-)	0.829	(-)	0.383	(-)	0.988	(-)
9	*ETHNIC*	0.428	(-)	0.864	(-)	0.340	(-)	0.243	(-)
10	*PCI*	0.388	(-)	0.252	(-)	0.156		0.079	
11	*VTOT*	0.339	(+)	0.120		0.558	(+)	0.817	(+)
12	*POP100CR*	0.308	(-)	0.847	(-)	0.606	(-)	0.149	
13	*SOILSUIT*	0.254	(-)	0.598	(-)	0.738	(-)	0.849	(-)
14	Initial income, 1960	0.080		0.016		0.000		0.000	
15	*RELIGION*	0.076		0.074		0.047		0.159	
16	Sub-Saharan Africa	0.075		0.382	(+)	0.032		0.000	
17	South Asia	0.053		0.112		0.438	(-)	0.018	
18	*EXEC*	0.048		0.000		0.163		0.147	
19	*FRTRADE*	0.031		0.022		0.294	(+)	0.000	
20	*COMP*	0.022		0.009		0.008		0.035	
21	Latin America &Caribbean	0.004		0.283	(+)	0.024		0.000	
22	*CMAP3*	0.000		0.000		0.025		0.039	
23	Middle East & N. Africa	0.000		0.194		0.000		0.000	
24	*ZTROPICS*	0.000		0.000		0.000		0.000	
25	*TROPICAL*	0.000		0.000		0.000		0.047	
26	*ZDRYTEMP*	0.000		0.177		0.018		0.000	
27	East Asia and Pacific	0.000		0.092		0.015		0.000	
28	*VREER*	0.015							
29	*Inflation volatility*			0.752	(+)				
30	*Volatility of fiscal policy*					0.460	(+)		
31	*Volatility of capital flows*							0.988	(+)

TABLE A3: ROBUSTNESS TO INDICATORS OF FINANCIAL DEVELOPMENT

Dependent Variable		VOL		VOL		VOL	
Sample		*Developing*		*Developing*		*Developing*	
Countries		*59*		*59*		*59*	
Variable		*(1)*		*(2)*		*(3)*	
1	*VTOT*	1.000	(+)	1.000	(+)	1.000	(+)
2	*ETHNIC*War*	0.923	(+)	0.770	(+)	0.778	(+)
3	War Dummy	0.923	(-)	0.770	(-)	0.778	(-)
4	*KKZ*	0.729	(-)	0.452	(-)	0.374	(-)
5	*SOILSUIT*	0.628	(-)	0.703	(-)	0.709	(-)
6	*FRTRADE*	0.581	(+)	0.644	(+)	0.519	(+)
7	*RELIGION*	0.519	(+)	0.311	(+)	0.290	(+)
8	Middle East & N. Africa	0.439	(+)	0.292	(+)	0.286	(+)
9	*POP60*	0.419	(-)	0.398	(-)	0.524	(-)
10	*DISTCR2*	0.330	(+)	0.559	(+)	0.600	(+)
11	*EXEC*	0.284	(-)	0.183		0.168	
12	South Asia	0.231	(-)	0.374	(-)	0.292	(-)
13	*CMAP3*	0.220		0.094		0.069	
14	*DISTCR*	0.143		0.352	(-)	0.391	(-)
15	*POP100CR*	0.098		0.101		0.081	
16	East Asia and Pacific	0.069		0.072		0.065	
17	*GTYPE*	0.068		0.142		0.202	(-)
18	*PCI*	0.051		0.142		0.152	
19	*ETHNIC*	0.051		0.106		0.160	
20	*ZTROPICS*	0.011		0.000		0.000	
21	*ZDRYTEMP*	0.009		0.000		0.000	
22	Sub-Saharan Africa	0.001		0.000		0.000	
23	*LANDLOCK*	0.000		0.239	(-)	0.319	(-)
24	*COMP*	0.000		0.018		0.000	
25	Latin America &Caribbean	0.000		0.000		0.000	
26	*TROPICAL*	0.000		0.000		0.000	
27	Initial income, 1960	0.000		0.000		0.000	
28	*PRIV*			0.427	(-)	0.215	(-)
29	*LLY*			0.045		0.037	
30	*PRIV Squared*					0.360	(+)
31	*LLY Squared*					0.085	

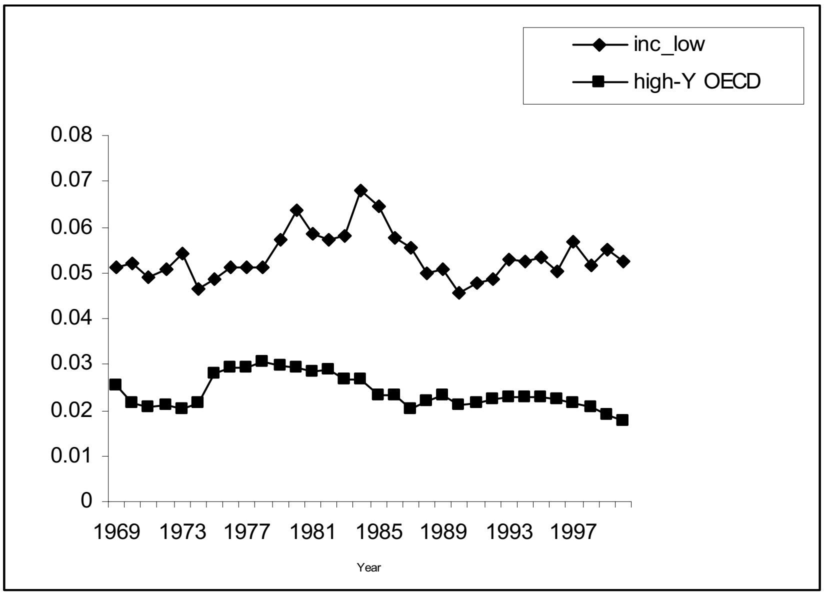
Stylized facts – material for working paper version

THE EVOLUTION OF VOLATILITY, BY LOCATION



Notes: Output Volatility is defined as the standard deviation of annual observations of growth of real GDP per capita during the period 1960-1999. Figures based on the rolling standard deviation of past ten years of data for each country; the median for each group used; KG-Tropical and Temperate are the Koeppen-Geiger eco-zone classification of the tropics and temperate regions, respectively.

THE EVOLUTION OF OUTPUT VOLATILITY, BY INCOME LEVELS



Notes: Output Volatility is defined as the standard deviation of annual observations of growth of real GDP per capita during the period 1960-1999. Figures based on the rolling standard deviation of past ten years of data on each country; the median for each group used; *Inc-Low* refers to low-income and *high-Y OECD* to high-income OECD countries, based on the World Bank definitions.

THE EVOLUTION OF OUTPUT VOLATILITY – *by region*

		1960-99		1960s		1970s		1980s		1990s	
	N	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Latin America & the Caribbean	25	.049 (.018)	.045	.036 (.019)	.030	.047 (.033)	.041	.050 (.020)	.043	.042 (.030)	.034
Sub-Saharan Africa	41	.077 (.031)	.071	.068 (.041)	.058	.074 (.038)	.073	.067 (.036)	.057	.068 (.059)	.055
South Asia	5	.032 (.006)	.032	.034 (.009)	.035	.036 (.019)	.029	.026 (.014)	.024	.021 (.008)	.023
East Asia & the Pacific	14	.043 (.016)	.038	.045 (.038)	.042	.033 (.013)	.032	.035 (.013)	.036	.039 (.021)	.033
Middle East & North Africa	10	.060 (.026)	.048	.065 (.040)	.049	.076 (.045)	.060	.048 (.028)	.035	.028 (.016)	.024
Western Europe & North America	18	.029 (.014)	.026	.028 (.019)	.025	.033 (.023)	.027	.023 (.007)	.022	.024 (.012)	.019

Notes for the tables

Output Volatility is defined as the standard deviation of annual observations of growth of real GDP per capita.
The statistics are reported for non-overlapping decades: 1960-69, 1970-79, 1980-89, and 1990-1999.
Figures in parentheses are standard errors.
Regions defined on the basis of World Bank classifications.

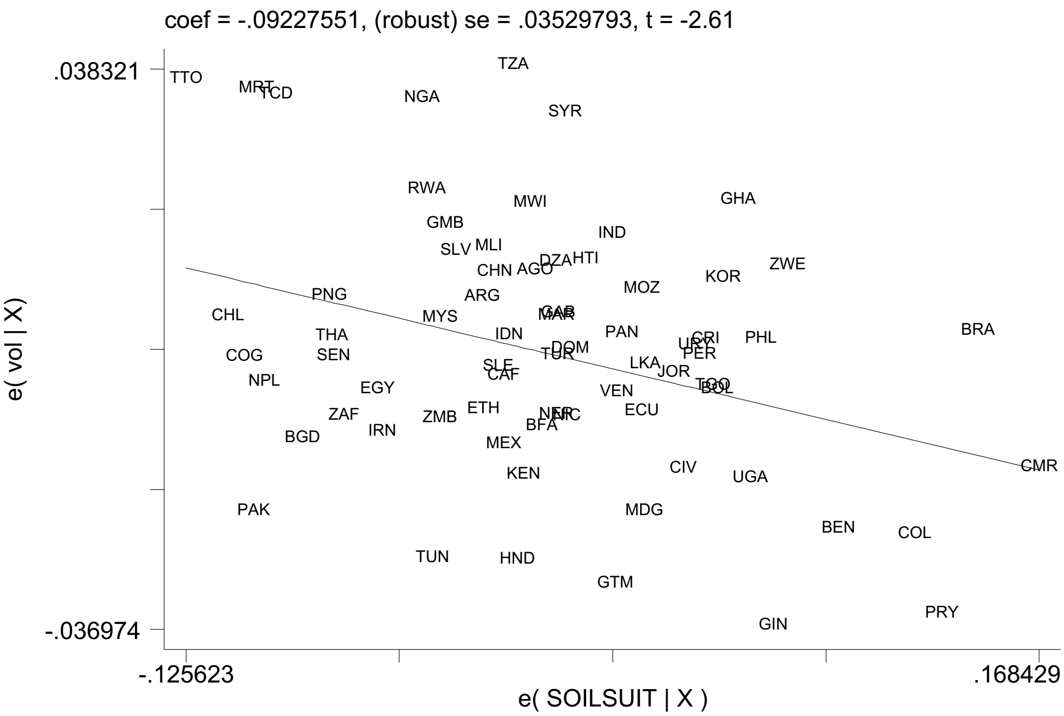
a. Figures for developing countries that are NOT "low-income".
b. Based on the tropical (0,1) dummy from Global Development Network database
c. Countries classified as non-tropical if 0 per cent of their area falls in the tropics-subtropics eco-zone. The rest are treated as tropical countries. A parallel definition is used for temperate and non-temperate zones.
d. Refers to non-fuel primary commodity exporters; the export classifications are from the World Bank.

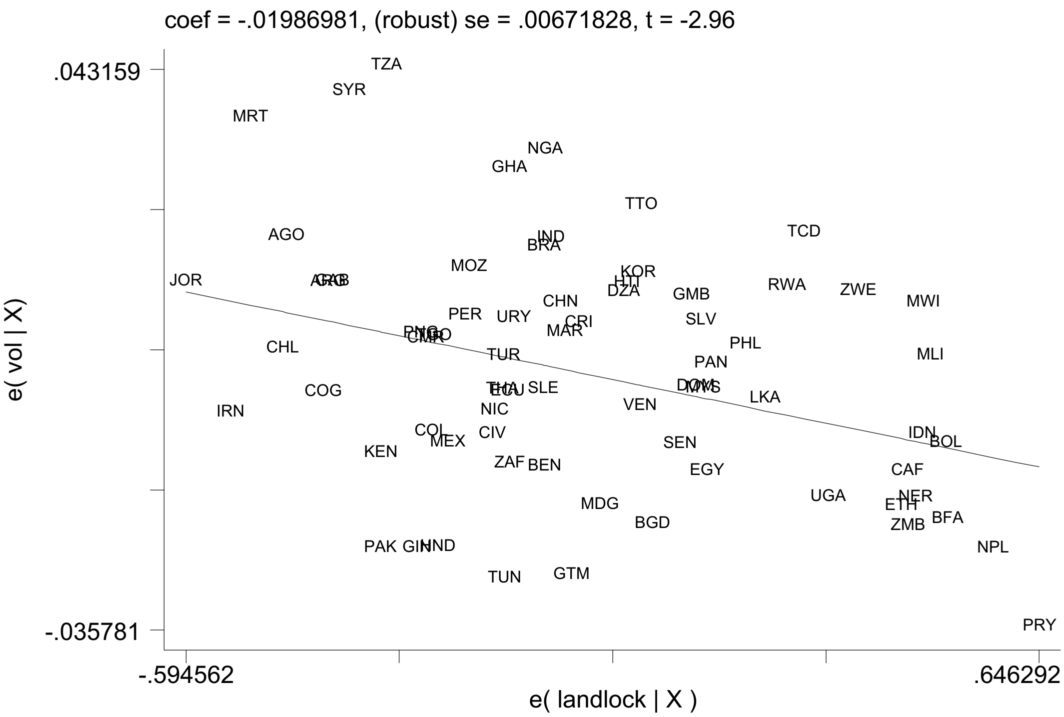
THE EVOLUTION OF OUTPUT VOLATILITY – *by decades*

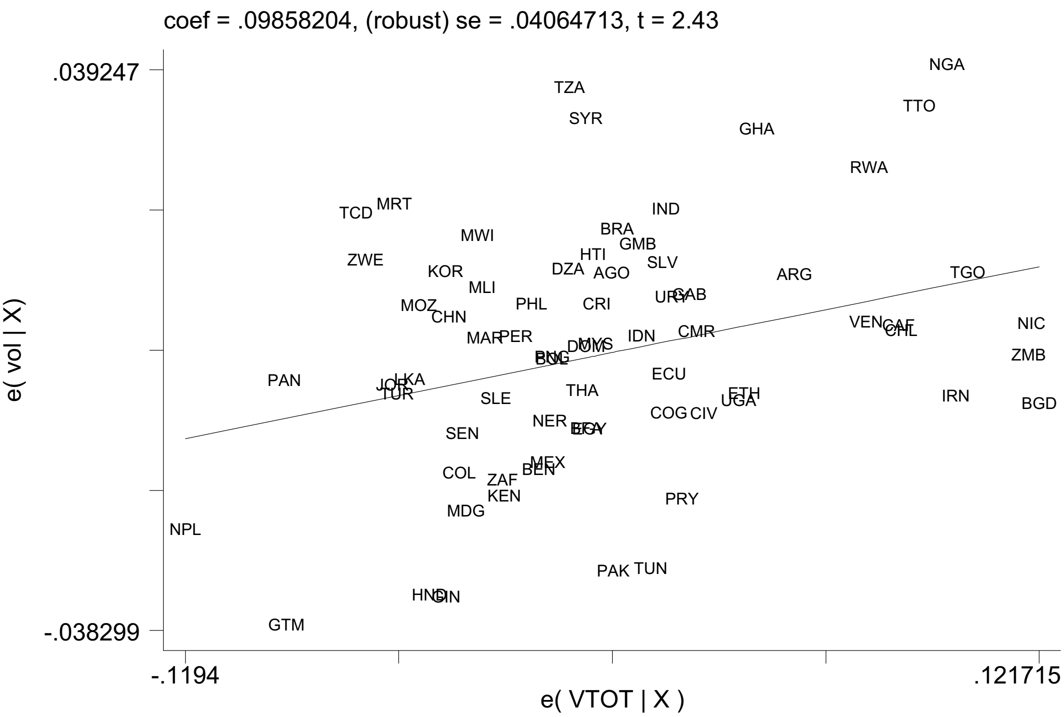
		1960-99		1960s		1970s		1980s		1990s	
	N	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
All		.055	.046	.050	.041	.054	.041	.050	.039	.046	.032
		(.029)		(.036)		(.036)		(.035)		(.043)	
Developing[a]	47	.054	.046	.047	.041	.053	.041	.058	.043	.044	.034
		(.028)		(.031)		(.037)		(.039)		(.042)	
Low-income	42	.069	.066	.062	.051	.068	.057	.058	.051	.062	.055
		(.029)		(.039)		(.038)		(.035)		(.049)	
High income OECD	22	.028	.026	.026	.025	.030	.030	.023	.023	.022	.019
		(.007)		(.012)		(.011)		(.007)		(.009)	
Tropical[b]	66	.065	.063	.057	.047	.061	.048	.059	.051	.057	.038
		(.031)		(.039)		(.038)		(.032)		(.051)	
Koeppen-Geigger											
Tropics-Subtropics [c]	70	.059	.052	.048	.042	.055	.042	.054	.044	.055	.035
		(.031)		(.029)		(.037)		(.033)		(.051)	
Non-tropics	34	.046	.038	.046	.033	.050	.034	.035	.026	.028	.024
		(.029)		(.042)		(.036)		(.023)		(.016)	
Temperate	42	.042	.036	.039	.030	.044	.032	.034	.028	.029	.026
		(.024)		(.028)		(.034)		(.019)		(.015)	
Non-temperate	62	.064	.061	.053	.042	.059	.049	.057	.049	.058	.038
		(.032)		(.037)		(.037)		(.034)		(.054)	
Key Export Categories											
Primary Commodity[d]	34	.072	.064	.060	.053	.066	.052	.064	.058	.067	.047
		(.035)		(.039)		(.039)		(.038)		(.061)	
Manufactures	16	.043	.037	.032	.025	.031	.032	.025	.021	.026	.023
		(.028)		(.017)		(.008)		(.011)		(.013)	
Fuel-exporters	8	.084	.085	.077	.066	.087	.094	.072	.070	.070	.049
		(.022)		(.045)		(.034)		(.031)		(.060)	

See notes on the previous page.

Added variable plots – material for working paper version



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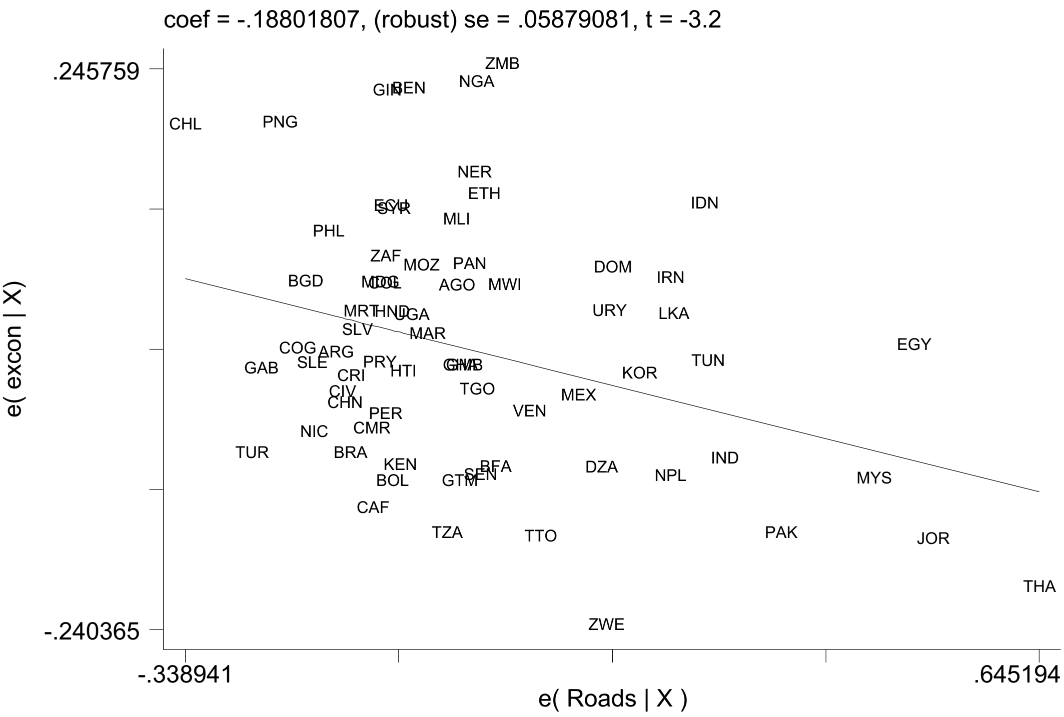
-.038299
e(vol | X)
-.1194
.121715
e(VTOT | X)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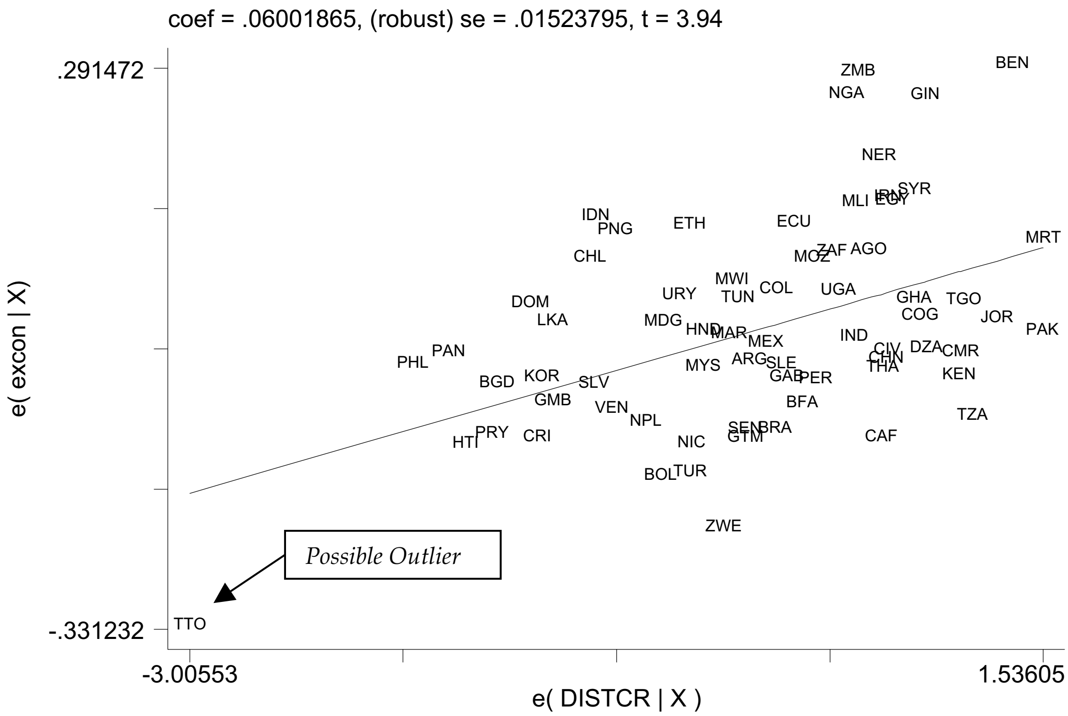
-.240365
e(excon | X)
-.338941
.645194
e(Roads | X)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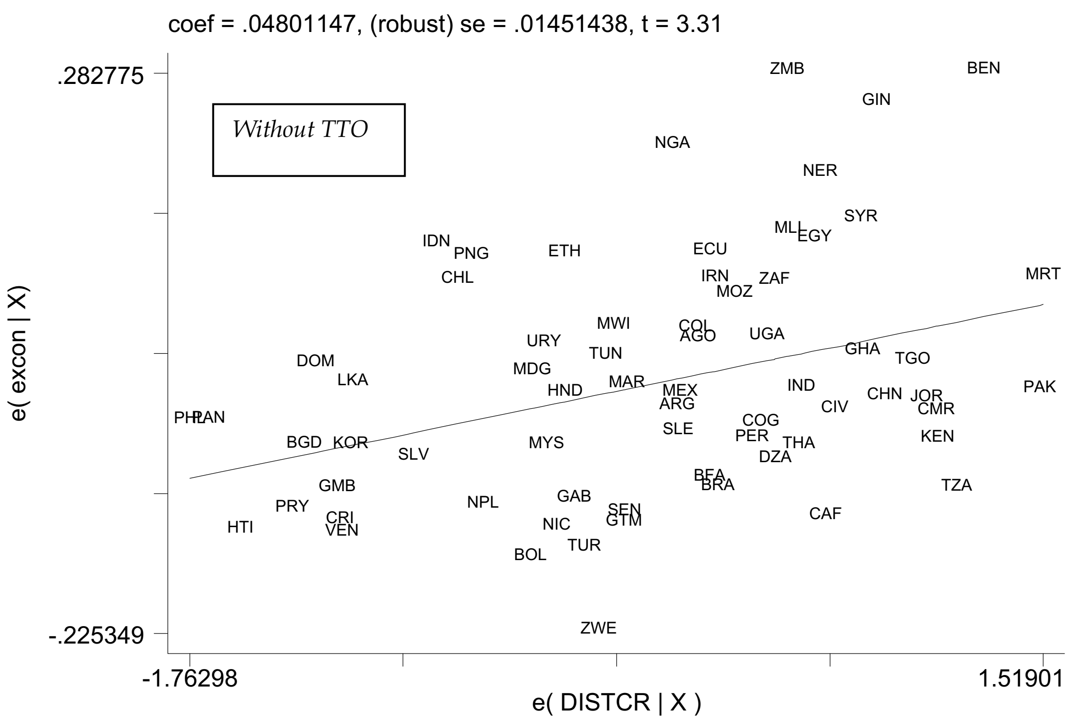
.291472
-.331232
e(excon | X)
-3.00553
1.53605
e(DISTCR | X)
Possible Outlier
TTO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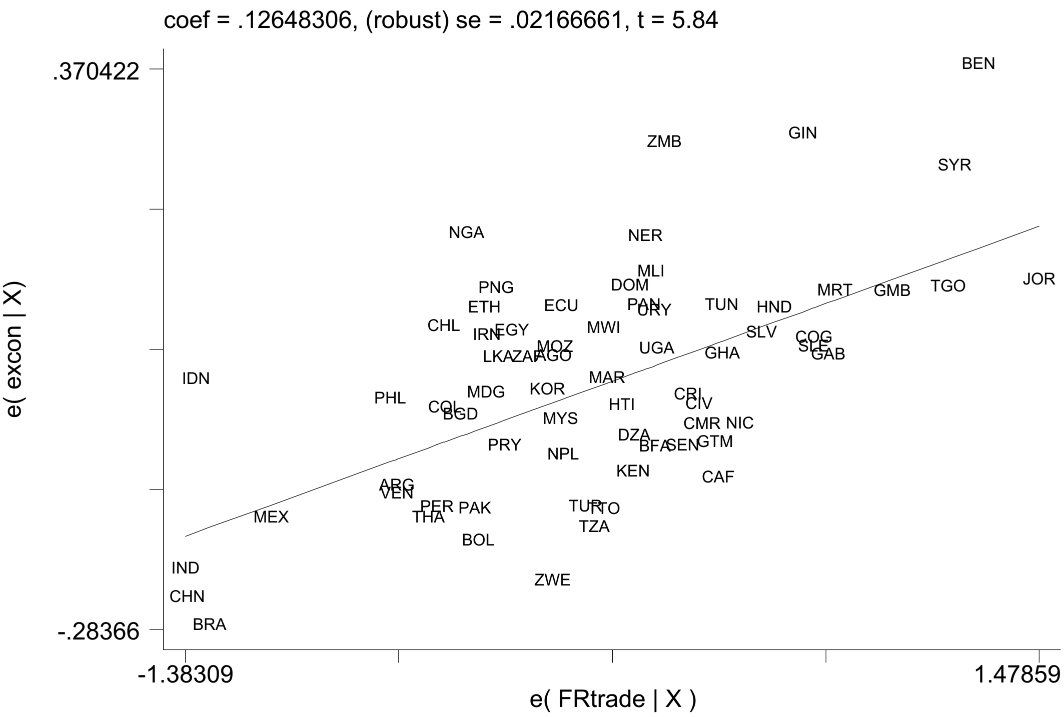
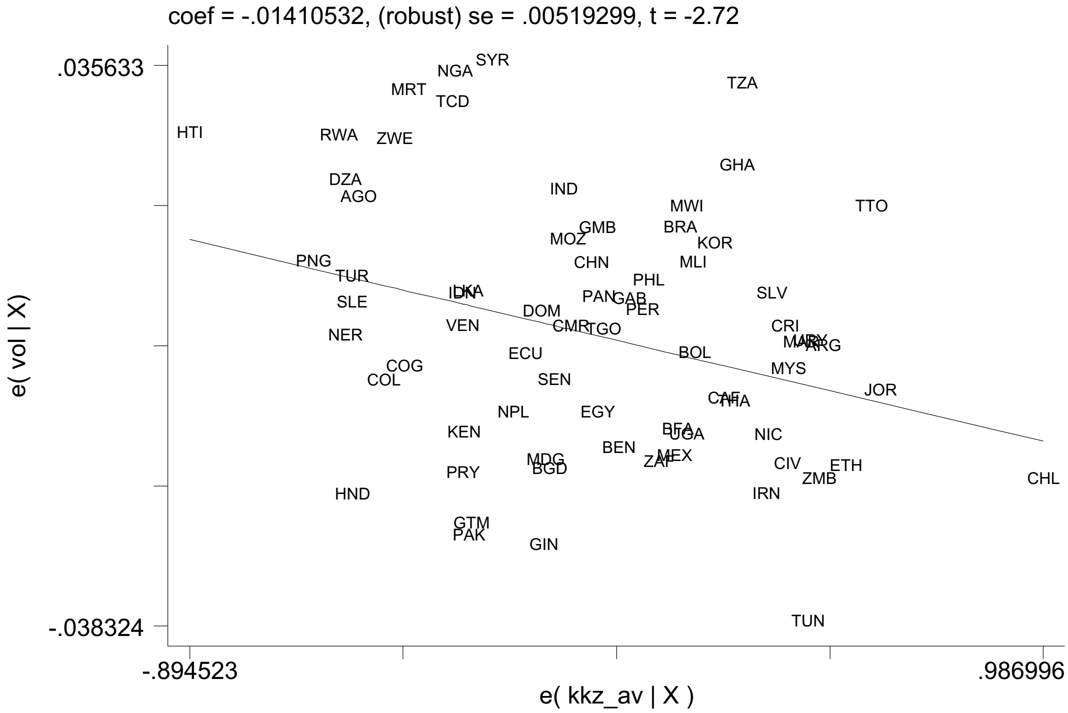
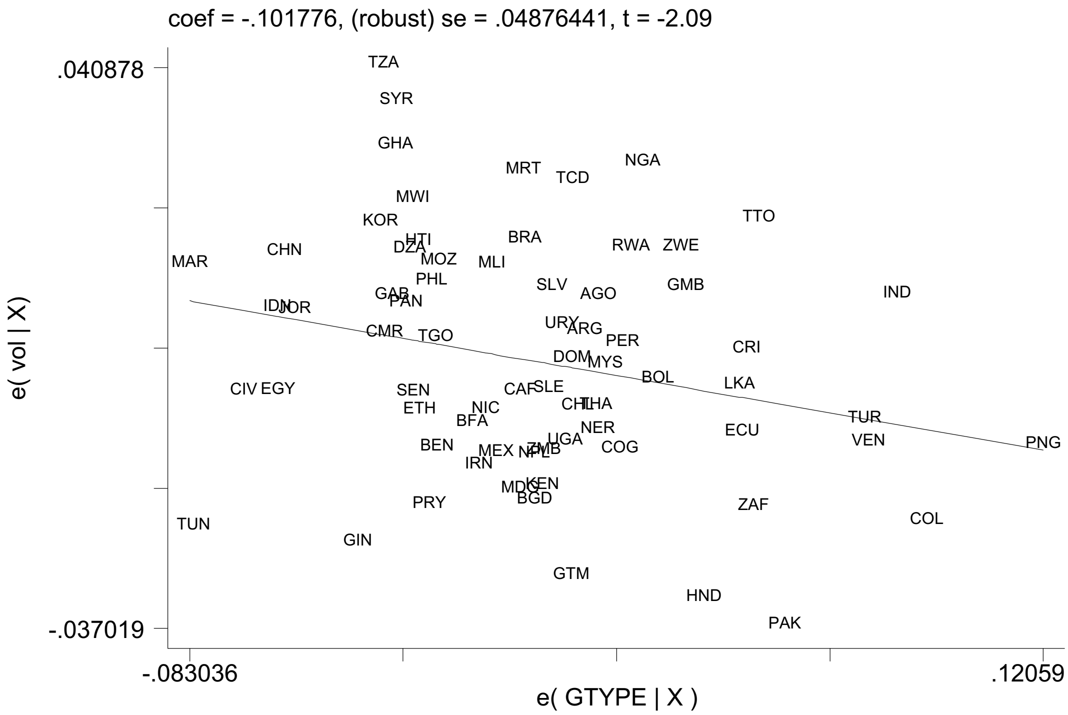
.282775
-.225349
e(excon | X)
-1.76298
1.51901
e(DISTCR | X)
Without TTO



coef = .12648306, (robust) se = .02166661, t = 5.84
.370422
-.28366
e(excon | X)
-1.38309
1.47859
e(FRtrade | X)
BEN
ZMB
GIN
SYR
NGA
NER
MLI
DOM
PNG
ECU
PAN
URY
TUN
HND
MRT
GMB
TGO
JOR
ETH
CHL
IRN
EGY
MWI
SLV
COG
SLE
GAB
MOZ
LKA
ZAF
AGO
UGA
GHA
IDN
MAR
PHL
MDG
KOR
CRI
CIV
HTI
COL
BGD
MYS
CMR
NIC
DZA
PRY
BFA
SEN
GTM
NPL
KEN
CAF
ARG
VEN
PER
PAK
TUR
TTO
MEX
THA
TZA
BOL
ZWE
IND
CHN
BRA


coef = -.01410532, (robust) se = .00519299, t = -2.72
.035633
-.038324
e(vol | X)
-.894523
.986996
e(kkz_av | X)
SYR
NGA
MRT
TCD
TZA
HTI
RWA
ZWE
GHA
DZA
AGO
IND
MWI
TTO
GMB
BRA
MOZ
KOR
PNG
CHN
MLI
TUR
PHL
SLE
PAN
GAB
PER
SLV
DOM
NER
VEN
CMR
TGO
CRI
ARG
ECU
BOL
COG
COL
SEN
MYS
JOR
NPL
EGY
THA
KEN
NIC
BEN
MEX
CIV
ETH
PRY
BGD
ZMB
CHL
HND
IRN
GIN
TUN

coef = -.101776, (robust) se = .04876441, t = -2.09
.040878
-.037019
e(vol | X)
-.083036
.12059
e(GTYPE | X)
TZA
SYR
GHA
NGA
MRT
TCD
MWI
TTO
KOR
BRA
CHN
RWA
ZWE
MAR
MOZ
MLI
PHL
SLV
AGO
GMB
IND
PAN
CMR
TGO
PER
CRI
DOM
MYS
BOL
LKA
CIV
EGY
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