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Abstract

Chapter 1: Economists examine two types of variables when studying aggregate production and economic growth. Factors which appear in standard Solow-type models (physical capital, labor, and human capital) are classified as direct inputs to production. Variables which affect aggregate output, but are not independently productive, are classified as indirect inputs. I introduce a flexible framework which allows indirect inputs to affect output through three channels: by altering total factor productivity, by changing factor-specific productivity (FSP), and by changing the incentive to accumulate direct inputs. An empirical application of the model to infrastructure, worker health, and childhood nutrition finds that indirect inputs have strong effects on the productivity of specific direct inputs. Non-nested hypothesis tests conclude that an FSP model is preferable to a model which includes the same indirect inputs in TFP. Higher levels and growth rates of indirect inputs are also shown to incentivize increased factor accumulation of direct inputs. Finally, these extensions produce more empirically realistic predictions for returns to scale and convergence than traditional neo-classical models.

Chapter 2: I extend the limited literature on international spatial economic growth by employing a clear procedure for model selection and highlighting the importance of using time fixed effects that are region specific. Using a sample of countries in the continental Americas, I find that after capturing shocks to the region with fixed effects, estimates of spatial effects are negative and significant, in contrast to most of the existing literature. The net economic value of these spatial effects is of a

magnitude similar to the value of the initial growth, and failing to account for growth spillovers is shown to bias estimates of the effectiveness of growth altering policies.

Chapter 3: I study a sample of quarterly and/or monthly data from 8 countries to address the question of how deficit uncertainty affects output growth. Uncertainty is measured using the conditional heteroskedasticity of the respective series. These measures are then incorporated in a VAR GARCH-M model. Results show that while deficit uncertainty does have a significant, negative effect on output growth in the US, this result does not hold universally. Evidence suggests that the effect may be unique to more developed countries. The magnitudes of uncertainty effects are demonstrated with a simulated one-time shock to the deficit and with a permanent shock to the overall level of deficit uncertainty.

Chapter 1: Factor-Specific Productivity

1.1 Introduction

Broadly speaking, recent literature regarding the vast differences in output which exist among countries has sought to 1) argue for the relative importance of either productivity differences or differences in factor accumulations across countries as the underlying cause of output differences and, 2) for those arguing for the importance of productivity differences, put forth an explanation of which variables may underlie the existing productivity differences. One way to categorize inputs to production is to ask the question, “Could this input produce output by itself?” For physical capital, human capital, and labor, the answer to this question is yes. These variables will be collectively referred to as direct inputs to the productive process. Any variable which affects production but could not produce output by itself will be referred to as an indirect input to production.

Most researchers add indirect inputs to regressions, either explicitly modeling them as affecting TFP or implicitly adding them in a manner consistent with independent TFP effects. However, I outline three ways in which indirect inputs could affect production. Indirect inputs could change total factor productivity, they could change the productivity of individual direct inputs, or they could incentivize or disincentivize accumulation of direct inputs.

In this paper I construct a framework which allows indirect inputs to influence a production function through any of these three channels. Arguably, this extension allows for modeling an indirect input in a manner which is consistent with the microeconomic theories regarding its effects. In an empirical application, I allow indirect inputs to alter the productivity of individual direct inputs rather than just the total factor productivity of the model. The included indirect inputs, each of which has previously been found to be correlated with output differences across countries, reflect infrastructure, worker health, and childhood nutrition. Furthermore, I separately show that higher levels of indirect inputs are correlated with higher future stocks of direct inputs and that indirect input growth incentivizes future growth in direct inputs.

The model which I introduce has three advantages over a standard model which includes the same inputs captured through a TFP term. First, my model reflects the channels through which microeconomic studies have found the indirect inputs operating. Including the indirect inputs in a TFP term captures neither the subtlety nor the specificity of indirect effects found at the individual level. Second, a Davidson and MacKinnon non-nested hypothesis test indicates that my FSP model is more appropriate than a model which allows only TFP effects in fitting the data. Evaluating the production function in levels, the FSP model is strictly preferred to the TFP model. In corresponding growth regressions, both FSP and TFP models have independent explanatory power. Third, from a policy perspective, the combination of better model performance and relevant connections to the microeconomic foundations may make an FSP model more useful for estimating aggregate impacts of micro policies focused on economic growth and development.

The rest of this paper is structured as follows. Section II provides a general overview of some of the existing literature on models which focus on differences in factor accumulation or differences in productivity in explaining cross-country outcomes. I also provide case studies using the microeconomic literature on how particular indirect inputs should affect production outcomes. Section III proposes a model for analyzing the effects of indirect inputs in production, both in levels and in growth rates. Section IV applies this model to three indirect inputs and empirically tests the FSP model against a TFP model. The robustness of the test result is checked under a number of specifications. Section V discusses the implication on returns to scale and convergence in this new framework. Section VI concludes.

1.2 Reviewing the Existing Literature

1.2.1 Stocks of direct inputs, productivity differences, and output differences

A few key works are responsible for advancing the debate on factor accumulation versus productivity differences. Strongly on the side that output differences are primarily the result of differing levels of direct inputs are works such as Mankiw, Romer, and Weil (1992), who estimate that 78% of the international variance in output can be explained by factor accumulation differences according to their famous augmented Solow model. Looking at a specific region, Alwyn Young (1994, 1995) further supports this theory in his finding that rapid factor accumulation seems to be the primary cause of the East Asian growth miracles. Nonneman and Vanhoudt (1996) find that the inclusion of "technological know-how" as a factor of production allows an augmented Solow model to explain three quarters of the variation in output among OECD countries.

Sturgill (2010) also argues that differences in factor accumulation, not productivity parameters, explain output differences across countries. His work is distinguished by the fact that factor shares (or specific factor productivity parameters) are not held to be constant through the development process. Instead, he shows that less developed countries observe higher returns to non-reproducible factors of production (labor and "natural capital"), while technological change in the development process actually shifts productivity away from the non-reproducible factors towards the reproducible factors (physical capital and human capital). I also allow for changes in the productivity of specific factors, and compare my results to those of Sturgill in Section IV. While Sturgill demonstrates how factor productivity differs across developed and developing countries, he does not go on to model how indirect inputs influence this difference.

The other side of the debate follows primarily from Hall and Jones (1999), who estimate the differences in productivity across countries as the residual from a Solow-type equation. They find that these differences, which are now commonly referred to as Total Factor Productivity (TFP), explain the largest portion of international output differences. Hall and Jones discuss "social infrastructure" factors which they feel are critical to explaining the cross-country differences in productivity. Similarly, Klenow and Rodriguez-Clare (1997) re-examine the approach of Mankiw, Romer, and Weil and, after small adjustments to data, argue that productivity differences, not factor accumulation, account for the majority of national income variations and call for additional focus on the causes of international productivity differences. In this line of research Robert Barro (1990, 1991, 1995, 1996, 1999, 2000, 2001, 2003, 2004; Barro & Sala-i-Martin, 1997) has written a series of empirical studies examining indirect inputs which are associated with growth differences across countries. If one takes the perspective that growth models are simply levels models of output viewed dynamically, these variables would be necessarily included in the productivity parameter in a production function approach. The list of variables Barro has examined include, but are not limited to, government consumption, political instability, market system, terms of trade, fertility rates, child mortality rates, inflation and its variability, life expectancy, educational spending, democracy, rule of law, intellectual property rights, research and development expenditures, income inequality, trade openness, and religion. Any or all of these variables could potentially help to explain the productivity differences across countries when appropriately included in a production function.

Two previous works have worked with similar models in order to look at indirect inputs and production or productivity. Dearmon and Grier (2009) estimate a reduced form model which allows for social capital to affect worker productivity, without attempting to generate a structural model which would correspond to their reduced form. Piper (2011) employs one special application of the general framework introduced here to examine the benefits of improved nutrition on aggregate productivity. In so doing, he uses a model which includes nutrition as an indirect input which affects the productivity of labor and of human capital, demonstrating how factor-specific models can be used evaluate microeconomic policies.

1.2.2 Infrastructure, Health and Nutrition in Development Accounting

Estache and Fay (2007) provide an excellent summary on the history of infrastructure's inclusion in growth and development debates as well as the current views on the topic. The literature suggests that the primary effects of improved infrastructure (especially measured by something like electrical capacity) should be on the productivity of firms through the types and effectiveness of available capital, although it can also affect investment adjustment costs, capital durability, and the supply and demand for health and education services, as well as the effectiveness of investments in education (Agenor & Moreno-Dodson, 2006; Brenneman, 2002). Infrastructure is a very inclusive term, and it is certain that no single measure can adequately capture the total infrastructure of a country. Some measures which are common in the literature include miles of roads or numbers of vehicle per capita, which measure some aspects of transportation infrastructure, coverage of telegraphs, telephones, or cellular phones, which capture communication infrastructure, and the availability of clean water or electricity, which are more general infrastructure measures. Because it is such a general measure, and because it has good data availability, I employ a measure of a country's electricity generating capacity for the empirical analysis. This data comes from David Canning's data set, updated from Canning (1998). As suggested by the microeconomic literature, the primary role of infrastructure relates to the effectiveness of physical capital, so the empirical analysis includes infrastructure in the factor-specific term for capital.

The net effects of infrastructure on growth or development have been much examined, although findings on the net returns have varied from negative or zero to positive and significant (Romp & de Haan, 2005; Straub & Vellutini, 2006; Biceno, Estache, & Shafik, 2004; Gramlich, 1994). There does, however, exist a growing consensus in the literature that, whatever the returns to infrastructure may be, they are likely not linear and may be dependent upon the levels of other inputs to production (Roller & Waverman, 2001; Fernald, 1999; Albala-Bertrand & Mamatzadakis, 2004).

Several papers have previously examined the relationship between aggregate health and aggregate production (Ashraf, Lester, & Weil, 2008; Bloom & Canning, 2005; Bloom, Canning, & Sevilla, 2004; Weil, 2007). Findings have ranged from no effect to small but significant positive returns to increased health. Unlike this paper, most of the previous literature has treated health as a direct input into production or as an indirect input affecting overall productivity.

For the purposes of this paper, health will refer to the overall health of current workers, specifically in ways which would affect their ability to engage in their normal tasks. To reflect overall worker health, I employ an estimate of average life expectancy, which is commonly used in macroeconomic analyses to reflect overall health conditions (e.g., Bloom and Canning (2005) and Ashraf, Lester, and Weil (2008)). Some of the commonly reported estimated effects of improved health are decreases in Years Lost to Disability (YLD), increased labor market participation, increases in worker performance while at work, increased savings, increased investments in human capital, and decreased fertility rates.

Because the greatest effects of improved health fall directly on workers, the health measure is included in the factor-specific productivity term on the labor supply, although I will also look at the effects of increased health on the accumulation of all three direct inputs.

Nutrition is one variable which has been somewhat absent from the literature on aggregate production despite a rich microeconomic literature focusing on the individual benefits to improved nutrition. While some authors group nutrition in with other health measures, the microeconomic literature suggests unique and important roles for nutrition distinct from other health measures, specifically in cognitive development in utero and in early childhood. This micro-founded literature has found significant effects of improved nutrition, especially early in life, on cognitive development, labor market outcomes, test scores, and grades completed (Alderman, Hoddinott, & Kinsey, 2006; Behrman, 2007; Behrman & Rosenzweig, 2004; Glewwe & King, 2001; Grantham-McGregor, Fernald, & Sethuraman, 1999; Grantham-McGregor et al. 2007; Johnston, Low, de Baessa, & MacVean, 1987; Maluccio et al. 2009; Strauss & Thomas, 1998; Victora, et al., 2008). Results seem especially strong for women (Maluccioet al., 2009). Taken together, the micro results suggest that the primary effects of nutrition are related to education and that increased nutrition affects both the returns to education for individuals and the accumulation of human capital. Nutrition will thus be included in the FSP term for human capital in the empirical analysis.

Piper (2011) looks at the aggregate effects of nutrition on country output, and finds that proper nutrition is key to making investments in human capital productive in the future, and that improved nutrition has strong effects on current worker productivity. This paper, like Piper (2011), allows the overall nutrition level to be captured by the average caloric intake of the population of a country.

1.3 A model for looking at indirect inputs

In developing a general model of production, I begin with an augmented Solow model of the form:

$$Y_{it} = A(K_{it})^{\alpha}(L_{it})^{\beta}(H_{it})^{\gamma} \tag{1.1}$$

Here, production in country *i* at time *t* is a function of direct inputs (labor (L), capital (K), and human capital (H)), along with some overall productivity scaling factor (A).

It is possible to extend this framework to allow for indirect inputs to affect production through three distinct channels. First, indirect inputs should be able to systematically influence the TFP term across countries. Therefore, instead of having a constant TFP term, A, total productivity will be a function of indirect inputs denoted A(•). This channel would be appropriate for modeling an indirect input which altered the overall productivity in a country. Consider, for example, an input which facilitated general technology transfer across countries.

Second, indirect inputs should be able to have heterogeneous effects on the productivity of each of the direct inputs to production. To achieve this, I replace the standard exponents α, β, and γ, with Factor-Specific Productivity (FSP) functions, α(•), β(•), and γ(•). Just as the standard exponents in Solow-type models have dual interpretations as both relative productivity parameters and factor income shares, the FSP functions have two interpretations: one interpretation reflecting heterogeneous relative factor productivities across countries and time and another interpretation as reflecting differing factor shares of income. This leaves my production function of interest as:

$$Y_{it} = A(\bullet)(K_{it})^{\alpha(\bullet)}(L_{it})^{\beta(\bullet)}(H_{it})^{\gamma(\bullet)} \tag{1.2}$$

The third way indirect inputs could potentially influence production is through the accumulation of the direct inputs, K, L and H. To account for this, I allow the growth of the direct inputs as to depend upon the levels and growth rates of indirect inputs in separate regressions.

Within the framework of equation (1.2), the researcher's discretion is still involved in the selection of which indirect inputs to examine, which of the four productivity functions each input should be included in, and the functional forms of the TFP and FSP functions. I endeavor to be guided in these choices by the existing literature and by microeconomic foundations.

I select three indirect inputs for inclusion in FSP terms. I include electricity generating capacity per capita as a measure of infrastructure. As the literatures suggests that infrastructure most strongly influences the returns to physical capital, electrical consumption is included in the FSP function $\alpha(\bullet)$. For simplicity, $\alpha(\bullet)$ is modeled as a linear function of infrastructure and a constant:

$$\alpha(\mathrm{INF}_{i,t}) = \alpha_0 + \alpha_1 \mathrm{INF}_{i,t} \tag{1.3}$$

To proxy for worker health, I include average life expectancy of a country's population as an indirect input modifying the FSP function for labor, $\beta(\bullet)$. While the life expectancy data in each year is intended as the projected life expectancy of babies born in that year, because it is calculated based on the existing health of the current population, it should be a good proxy for the health of current workers. $\beta(\bullet)$ is a linear function of this measure of worker health and a constant[1]:

[1] Alternative specifications where $\alpha(\bullet)$ and $\beta(\bullet)$ included the indirect inputs squared were tested as well. Results are highly similar to those presented here, and are available upon request.

$$\beta\left(\mathrm{HEALTH}_{i,t}\right) = \beta_0 + \beta_1 \mathrm{HEALTH}_{i,t} \tag{1.4}$$

As a measure of childhood nutrition I include the average caloric intake within a country, lagged 15 years. I scale the caloric value relative to a recommended intake of 2500 calories daily. To account for the decreasing returns to average nutrition, the square root is then taken of this scaled value, and I label the result RDA. Childhood nutrition, as indicated by the microeconomic literature, affects the returns to educational investments by individuals and is thus included in the FSP term for human capital, $\gamma(\bullet)$, along with a constant.

$$\gamma\left(\mathrm{RDA}_{i,t-15}\right) = \gamma_0 + \gamma_1 \mathrm{RDA}_{\,i,t-15} \tag{1.5}$$

$$\mathrm{RDA}_{i,t-15} = \left(\frac{\mathrm{NUTR}_{i,t-15}}{2500}\right)^{1/2} \tag{1.6}$$

For the purposes of my model, TFP will be represented by a constant, e^{A}. TFP will be considered constant both across countries and through time. I will compare this very restrictive specification to others where TFP varies according to the levels of indirect inputs. For robustness, I will also check my model against alternative models where TFP is additionally allowed to have country or year fixed effects.

Traditionally, production functions are rewritten so that direct inputs and resulting GDP can be expressed in per-capita or per-worker terms. However, by allowing FSP functions to vary across countries and across time, it becomes impossible to cleanly divide through by population or by the labor force. It is important to keep in mind that results should be interpreted in terms of overall production, not output per capita. So, replacing the FSP functions in the production function in (2) we can write:

$$Y_{it} = \mathrm{e}^{\mathrm{A}}(K_{it})^{\alpha_0+\alpha_1\mathrm{INF}_{\mathrm{i,t}}}(L_{it})^{\beta_0+\beta_1\mathrm{HEALTH}_{\mathrm{i,t}}}(H_{it})^{\gamma_0+\gamma_1\mathrm{RDA}_{\mathrm{\ i,t-15}}} \tag{1.7}$$

For estimation purposes, natural logs are taken of both sides of equation (1.7) yielding:

$$y_{it} = \mathrm{A} + \alpha_0 k_{\mathrm{i,t}} + \alpha_1 \mathrm{INF}_{\mathrm{i,t}} k_{i,t} + \beta_0 l_{i,t} + \beta_1 \mathrm{HEALTH}_{\mathrm{i,t}} l_{i,t} + \gamma_0 h_{i,t} + \gamma_1 \mathrm{RDA}_{\mathrm{\ i,t-15}} h_{i,t} \tag{1.8}$$

where lowercase variables represent the natural logs of their uppercase counterparts. Equation (1.8) represents my primary FSP model in levels. Additionally, I will examine the FSP model in growth rates after rewriting the interaction terms as single variables. $\mathrm{INF}_{\mathrm{i,t}} k_{i,t}$ is rewritten simply as $\mathrm{Effective\ Capital}_{\mathrm{i,t}}$ and is abbreviated $EK_{i,t}$. Similarly, the HEALTH/labor and RDA/human capital interactions are renamed $\mathrm{Effective\ Labor}_{\mathrm{i,t}}$ and $\mathrm{Effective\ Human\ Capital}_{\mathrm{i,t}}$ and are abbreviated as $EL_{i,t}$ and $EH_{i,t}$ respectively. The corresponding FSP growth equation can then be written as:

$$\%\Delta y_{i,t} = \alpha_0 \%\Delta k_{i,t} + \alpha_1 \%\Delta EK_{i,t} + \beta_0 \%\Delta l_{i,t} + \beta_1 \%\Delta EL_{i,t} + \gamma_0 \%\Delta h_{i,t} + \gamma_1 \%\Delta EH_{i,t} \tag{1.9}$$

I now move to an empirical investigation of the benefits of my model.

1.4 The Effects of Infrastructure, Worker Health, and Childhood Nutrition on Production

1.4.1 Primary Regression Results

I estimate equation (1.8) on an unbalanced panel of countries at five year intervals over the time period 1980-2000, for a maximum of five observations per country. Eighty-eight countries are included.[2] Data on the stocks of physical and human capital are included along with estimates of the labor force, following Benhabib and Spiegel (1994). While this approach differs from most existing work, which instead includes estimates of factor income shares, it allows for an explicit estimation of the elasticities of outputs with respect to inputs (Temple, 1999). The stock of physical capital is constructed by a perpetual inventory method using a 5% depreciation rate. The reader is referred to the data appendix for full information on the construction and sources for all variables and a list of which countries are included in the sample.

In considering specifications (8) and (9), it seems apparent that the dependent variables and many of the right hand side variables may be simultaneously determined, leading to endogeneity concerns. This potential endogeneity could be coming from two sources. First, un-modeled factors could systematically influence both the dependent and RHS variables. This concern would apply to the model in levels but not to the growth model if the un-modeled factors were time invariant. Endogeneity could also occur if RHS variables were, in part, determined by contemporaneous levels of income. This concern applies equally to both the level and growth models, and needs to be

[2] The countries which are included are all of those which have enough observations in each of the variety of sources from which I am drawing in order for each country to have more than one complete observation.

addressed through instrumentation. I consider instrumentation potentially necessary for the stock of physical capital (k), electricity generating capacity (INF), the labor supply (l), life expectancy (HEALTH), and the stock of human capital (h). RDA is already constructed with a 15 year lag and so it seems unreasonable that current income could be influencing it.

For instruments, I utilize variables on population age distributions. These variables reflect the fraction of a country's population in each 5 year bin from ages 0-80. Cook (2002) points out that life cycle theories tie savings and investment to the population age structure. Empirical evidence of this relationship is found in Higgins (1998). This relationship makes the age distribution appropriate as instruments for both the stock of physical capital and the infrastructure level. Because the fraction of young people in schools has increased over time, the age distribution should also be related to the human stock of capital. Age structure has previously been used as an instrument for human capital stocks in Ciccone and Peri (2006). Life expectancy estimates take into account the existing population's age structure, and models of labor force participation establish a relationship between age structure and participation as well (Toossi, 2011). Wilson (2000) provides additional motivation for the relationship between demographic variables and factor inputs. Considering all of this evidence, the age structure data has an established relationship with all of the potentially endogenous variables. Moreover, changes in age structure are primarily the result of outcomes, shocks, and decisions sufficiently in the past that the data should pass the exclusion restriction for an appropriate instrument as well.

The age distribution instruments are constructed using the United Nations' *World Population Prospects: The 2010 Revision*. This data set provides the distribution of each country's population into 5 year age categories from ages 0-80 and a single category for those age 80+. Because this age distribution data is encompassed by 17 different variables, it can be used to instrument for all of the potentially endogenous variables. For technical details on the formation of the IVs, the reader is referred to Appendix 2. Table 1.1 provides summary statistics on the levels and growth rates of the variables of interest for the full sample period.

Table 1.2 presents the results of my instrumented regression from (8). Standard errors are included in parentheses below the point estimates. First stage estimates of model fit for both the FSP levels and FSP growth regressions are included in Table 1.3. A Hausman test, conditioned upon having appropriate instruments, strongly rejects the null hypothesis of no endogeneity in the levels regression.

The results of the FSP levels regression indicate that, by itself, the capital stock is significant in determining output, with a coefficient of 0.430. The supply of labor has a coefficient of 0.520, also statistically significant. The stock of human capital, by itself, has a negative and significant effect on output with a coefficient of -0.188. The significance of physical capital and negative coefficient on human capital are common in much of the literature regarding development and are not unexpected. The discussion of the negative coefficient on human capital goes back to Islam (1995) and is further discussed in Pritchett (2001). Pritchett suggests that this result may be due to perverse institutional environments, the supply of educated labor expanding while demand remained constant, or educational quality having been so low that years of schooling create no human capital, an explanation consistent with this work. The approximate magnitudes of these coefficients on direct inputs are not out of line with other estimates. The more interesting variables within the model are the three indirect inputs. Better infrastructure is associated with higher productivity of physical capital, but the interaction term is not statistically significant. I will show in the next section that this result is due, in part, to heterogeneous effects of improved infrastructure in developed and developing countries.

As would be predicted, improved worker health is positively associated with labor productivity. This relationship is not only statistically significant, but also economically meaningful. The estimated coefficient implies that a one standard deviation increase in life expectancy (about 11 years) would increase the productivity of labor by about .015. From an alternate perspective, you could interpret this as indicating that a one standard deviation improvement in health increases the labor share of income by 1.5%.

Nutrition, also as predicted, has a positive and significant effect on the FSP of human capital. With caloric intake at or above recommended levels, the effect of nutrition largely offsets the negative estimated coefficient on human capital independent of nutrition. The exact magnitude of the effects of improved nutrition is sensitive to several factors, including how caloric intake is scaled to reflect diminishing returns and the ratio of developed to developing countries in the sample. However, the positive and significant coefficient on nutrition is not sensitive to changes in sample or specification. The combined results on indirect inputs would support the conclusion that the model is capturing the predicted effects these inputs should have on productivity.

The three indirect inputs which I examine serve as first step for studying the aggregate productivity effects of indirect inputs in general, but many other variables can be included within the framework of my model. However, in addition to estimating the effects of these three indirect inputs, this paper proposes an alternative model which hopefully can add to the explanatory power of existing production functions. An improved model of production allows for a better understanding of the development process and, importantly, allows for better estimates of the effects of development policies targeting indirect inputs. While I have already shown how this new model is able to theoretically reflect microeconomic effects of indirect inputs in a broader and potentially more appropriate manner than a baseline model using TFP, it remains to be demonstrated that these additions provide a more appropriate empirical description of the growth process than a model which includes the same indirect inputs as independent determinants of TFP as opposed to determinants of FSP.

Because the model specification in equation (1.2) could encompass my FSP model of output, a more traditional TFP model, or a combination of the two, a natural test would be to nest the two and see where the data indicates statistical significance. However, the multicollinear nature of the data makes it impossible to interpret findings when the indirect inputs are included in several different forms. Instead, I turn to the non-nested models test of Davidson and MacKinnon (1981). They propose a test of two models each seeking to explain the same outcome whereby the dependent variable is regressed on all variables which are included in model A but not model B. The fitted values of this regression, called $\hat{y}_A$, are then included in a regression of the outcome on all the variables of model B and $\hat{y}_A$. If the fitted values have a statistically insignificant coefficient, then model A adds nothing to model B. If the coefficient is significant, then model A does add to B. The test is then repeated with A and B switching places in the process. The dependent variable is regressed on those explanatory variables unique to model B, and the fitted values $\hat{y}_B$, are formed. These fitted values are added to model A, and their significance is tested. Once completed, there are four possible results of the test: First, A could add to B, but not vice versa, indicating that A is the preferred model. Second, B could add to A, but not vice versa, indicating that B is the preferred model. Third, both models could significantly add to the other, indicating that neither is preferred by itself but rather each has independent explanatory power, or fourth, neither model could add to the other, also indicating that neither is strictly preferred.

While these last two cases are not informative in picking one model over another, they are still useful in my specific case because they would justify the simultaneous inclusion of TFP and FSP effects in a production function. I apply the Davidson and MacKinnon test to two models, my preferred model resulting from equation (1.8), and a second model where all the indirect inputs are instead included in the TFP term, A(∙), as in equation (1.10).

$$y_{it} = \mathrm{A}_0 + A_1\mathrm{INF}_{\mathrm{i,t}} + \mathrm{A}_2\mathrm{HEALTH}_{\mathrm{i,t}} + \mathrm{A}_3\mathrm{RDA}_{\ \mathrm{i,t-15}} + \alpha_0 k_{\mathrm{i,t}} + \beta_0 l_{i,t} + \gamma_0 h_{i,t} \qquad (1.10)$$

The results of the Davidson and MacKinnon test can be seen in Table 1.4, and indicate that my model of FSP is strictly preferred to a model where the inputs are solely modeled as a part of TFP. In practice, while it might be extreme to claim that these three indirect inputs have no effect on TFP, the test does indicate that the primary effects of these indirect inputs are better reflected in factor-specific productivity, and thus if they can only be included in one portion of the production function, FSP terms are the appropriate forms.

Recall that in my model, TFP is treated as a constant, while FSP varies across countries and time. The Davidson and MacKinnon test above compares my model to one in which FSPs are constant while TFP varies along with the indirect inputs. For robustness, I retest my model against specifications in which the TFP function includes not only the indirect inputs, but also time and/or country fixed effects. When either time or country fixed effects are included, the result of the test is unchanged. My model continues to be strictly preferred to the model where TFP varies.[3] When both time and country fixed effects are included, neither model is preferred with a traditional 10% cutoff for statistical significance. However, the added term from my model has a p-value of 0.17 while the added term from the alternative model has a p-value of 0.5, still indicating support, albeit weaker, for my model over the alternative.

I additionally test the robustness of the Davidson and MacKinnon test to different specifications of the forms of indirect inputs by allowing for the indirect inputs to enter as natural logs instead. Changing both my model and the alternative to instead include ln(INF), ln(HEALTH), or ln(RDA) in any combination, the test in every case indicates that my model is preferred.

1.4.2 Model fit for OECD and NON OECD countries

Different production functions will provide a much better fit for the outcomes in some countries than the outcomes in others. Often, the groups of countries for which fit

[3] Results not presented here, but are available upon request.

is particularly good or poor may have observable characteristics in common such as level of development or geographic region. In fact, it is still under much debate whether a single function can describe the production of different nations, specifically developed and developing nations simultaneously. Sturgill (2010) investigates this question specifically, and finds that the productivity of direct inputs changes over the course of the development process. In particular, he finds that, after separating the factors of production (direct inputs) into reproducible factors (physical capital and human capital) and non-reproducible factors ("natural capital" and labor), that non-reproducible factor shares (and productivity) decrease with development while reproducible factor shares increase with development. I examine these results within the context of my model by re-estimating equation (1.8) on subsamples of OECD and NON-OECD countries separately. Results are found in Table 1.5.

By separating the subsamples, differences become apparent when examining both the coefficients of the direct inputs and of the indirect inputs as well. Consistent with the findings of Sturgill (2010), physical capital and human capital (as reproducible factors) have much higher estimated shares in the OECD subset, while labor, a non-reproducible factor, has a much higher share in the NON-OECD subset. This finding indicates that FSP terms should include more variables reflecting those factors which distinguish OECD and NON-OECD countries if the samples are going to remain grouped. At the very least, an OECD dummy could be included in the FSP functions. As for the indirect inputs, the estimated effects of improved health and nutrition are stronger in NON-OECD countries, while the effects of improved infrastructure are stronger in OECD countries. From a policy perspective, these results would support a claim that efforts in developing countries aimed at increasing production would do well to focus on investing in indirect inputs which improve the productivity of individuals instead of investing in physical capital or increased infrastructure. From a modeling perspective, the differing results for OECD and non-OECD countries indicate that additional non-linearities should be investigated in the FSP functions for the model to apply optimally to all countries.

1.4.3 Growth Regression results

Table 1.6 contains FSP regression results using the growth specification in equation (1.9). Were the production function perfectly specified, these results would be exactly the same as the corresponding estimates from the level regression. However, with weaker first stage results and a production function of only three indirect inputs, coefficients will likely not be identical. Still, results should be largely similar. In fact, with the exception of the coefficient on capital growth being small and insignificant, the results in Table 1.6 are relatively close to those in Table 1.2. Combined growth in capital and infrastructure leads to economic growth as well. Labor growth has positive and significant productivity and labor productivity increases with better worker health. Human capital investments have negative and significant returns by themselves but this is offset in part by investments combined with appropriate nutrition.

Again, it is important to determine whether a model of factor specific productivity is any improvement over a model using the same variables as part of a more traditional TFP term. Table 1.7 contains the results from repeating a Davidson and MacKinnon test, this time with my model in growth rates.

In this case, the test indicates that both the FSP model and the TFP model have unique explanatory power. Therefore, the evidence on growth rates would indicate that a general model as in equation (1.2) which allows for both types of effects would be ideal in circumstances where it can be practically applied.

1.4.4 Factor accumulation results

So far, I have allowed for two of the three potential effects of indirect inputs on production: TFP effects and FSP effects. I now turn to the third potential effect, that indirect inputs may incentivize the future accumulation of direct inputs. To investigate this potential, I introduce new equations relating the levels and growth rates of the direct inputs to the prior levels and growth rates of the three indirect inputs, INF, HEALTH, and RDA. Equations (1.11), (1.12), and (1.13) provide evidence relating the levels of direct inputs and the prior levels of indirect inputs. Equations (1.14), (1.15), and (1.16) are the corresponding growth equations relating direct input growth rates to the past growth of indirect inputs.

$$k_{i,t} = \delta_0 + \delta_1 INF_{i,t-5} + \delta_2 HEALTH_{i,t-5} + \delta_3 RDA_{i,t-15} \tag{1.11}$$

$$h_{i,t} = \theta_0 + \theta_1 INF_{i,t-5} + \theta_2 HEALTH_{i,t-5} + \theta_3 RDA_{i,t-15} \tag{1.12}$$

$$l_{i,t} = \varphi_0 + \varphi_1 INF_{i,t-5} + \varphi_2 HEALTH_{i,t-5} + \varphi_3 RDA_{i,t-15} \tag{1.13}$$

$$\%\Delta k_{i,t} = \delta_1 \%\Delta INF_{i,t-5} + \delta_2 \%\Delta HEALTH_{i,t-5} + \delta_3 \%\Delta RDA_{i,t-15} \tag{1.14}$$

$$\%\Delta h_{i,t} = \theta_1 \%\Delta INF_{i,t-5} + \theta_2 \%\Delta HEALTH_{i,t-5} + \theta_3 \%\Delta RDA_{i,t-15} \tag{1.15}$$

$$\%\Delta l_{i,t} = \varphi_1 \%\Delta INF_{i,t-5} + \varphi_2 \%\Delta HEALTH_{i,t-5} + \varphi_3 \%\Delta RDA_{i,t-15} \tag{1.16}$$

Results from these six regressions are found in Table 1.8. The regressions in levels are suggestive of a relationship between indirect inputs and factor stocks. Higher levels of infrastructure show no significant relationship with any of the factor supply measures. Improved health is correlated with higher stocks of both physical and human capital, consistent with the idea that longer-lived individuals will invest more in both types of capital. Higher levels of past nutrition are correlated with increased stocks of physical capital.

The factor models in growth rates are expected to be preferable to the models in levels because they difference out any time-invariant omitted variables. The differencing process also alleviates any concerns that the right hand side variables are endogenous because levels of direct inputs and indirect inputs are both being determined by some third factor. The factor growth regressions show that past growth rates of indirect inputs are strongly related to future growth of direct input stocks. All three indirect inputs have a statistically significant relationship with all three future direct input growth rates. The strongest effects of improved infrastructure are on the growth rate of capital, and the strongest effects of improved past nutrition are on the accumulation of human capital. Both of these results are consistent with what the microeconomic literature would suggest. The largest magnitude effects overall though, come from improvements in health. A one percent increase in life expectancy is associated with greater than one percent growth of all three direct inputs in the future. This suggests that models which fail to account for the factor accumulation effects of increases in indirect inputs like health might significantly underestimate the net macroeconomic benefits of these inputs.

1.5 Factor-Specific Productivity, Returns to Scale, and Convergence in Output

Many models of aggregate output imply that returns to scale are constant across all countries. In the case of the Solow models, the implication is that all countries have constant returns to scale. Other models have been developed specifically to have increasing returns to scale for all countries. One result of having the same returns to scale across nations is that these models imply convergence of output across countries, at least conditional upon the convergence of the direct inputs. Feyrer (2007) and Grier and Grier (2007) test these implications to critique Solow based models, finding that despite the convergence of direct inputs (and many indirect inputs as well), output simply is not converging. This, of course, leads to the question of why output does not converge. The FSP model would suggest that output should not be converging across countries because the returns to scale in production are not the same for all countries, or even within a single country through time. By construction, returns to scale should vary in the same way that FSPs vary, namely through differing levels of indirect inputs. If two countries have different infrastructure levels, for example, then their returns to capital should differ and, if they differ enough, convergence in output should not be expected even if capital stocks converge.

Using the significant coefficients from the FSP model in Table 1.5, I calculate a returns to scale parameter as the sum of the net exponents from the original production function for the OECD and non-OECD subsets. For non-OECD countries, this estimated parameter ranges from 0.922 to 1.028, indicating that non-OECD countries may experience constant or slightly diminishing returns to scale. For OECD countries, the parameter ranges from 1.087 to 1.114, indicating that more developed countries all experience increasing returns to scale. This would be a possible explanation for the divergence of income noted by Grier and Grier (2007) and Feyrer (2007). If OECD countries have slightly increasing returns to scale while non-OECD countries have decreasing or constant returns to scale because of indirect inputs to production, even though non-OECD countries are closing the gap in terms of stocks of productive inputs, OECD countries could be pulling away in terms of income levels as a result of stronger returns to scale.

1.6 Conclusions

The development literature has debated whether cross-country output differences are driven by the accumulation of direct inputs or by productivity effects of indirect inputs almost continuously over the past twenty years. I propose a framework where indirect inputs have three effects. They can alter the Total Factor Productivity of all the direct inputs simultaneously, they can change the Factor-Specific Productivity of one or more direct inputs in different magnitudes, or they can incentivize the accumulation of direct inputs. The introduction of FSP allows for a more nuanced inclusion of indirect inputs which reflect the microeconomic channels through which they work.

Using three indirect inputs as examples, I employ the non-nested hypothesis test proposed by Davidson and MacKinnon to compare an FSP model against a more traditional TFP model including the same indirect inputs. The test finds that the FSP model outperforms the TFP model in levels, while both models have unique explanatory power in growth rates. This suggests that, data permitting, both forms of productivity effects should be included simultaneously. These results are robust across a variety of specifications. I also document how the indirect inputs appear to have significant effects, in both levels and growth rates, on the future accumulation of direct inputs.

Finally, this analysis highlights how a model with FSP terms can be used to explain the observation that, while the per capita stocks of direct inputs have been converging across countries, output has diverged. This prediction arises from eliminating the common restriction that returns to scale should be the same across countries. Instead, an FSP model suggests that returns to scale should differ systematically across countries and time because of differences in indirect inputs of production, and that convergence will not occur if returns to scale differ enough.

Future research should expand upon the indirect inputs included in the production function within the framework introduced here. Initial investigations in this direction could be guided by both the microeconomic literature about the indirect inputs and by the existing aggregate literature on which indirect inputs are most robustly related to output.

Table 1.1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max
Y	313 billion	972 billion	917 million	11.1 trillion
Capital	945 billion	299 billion	661 million	325 trillion
Labor	13.5 million	38.2 million	106 thousand	387 million
Human Capital	83.4 million	220 million	288 thousand	1.83 billion
INF	0.00069 megawatts	0.0010 megawatts	0.0000023 megawatts	0.0062 megawatts
HEALTH	64.72 years	10.93 years	29.10 years	81.08 years
RDA	0.998	0.098	0.793	1.120
%Δy	0.142	0.138	-0.551	0.546
%Δk	0.144	0.117	-0.136	0.551
%Δl	0.120	0.073	-0.255	0.463
%Δh	0.215	0.121	-0.234	0.735
%ΔINF	0.090	0.239	-0.844	1.783
%ΔHEALTH	0.017	0.042	-0.357	0.391
%ΔRDA	0.011	0.034	-0.121	0.119

Table 1 shows the summary statistics for the variables of interest for the full sample from 1980 to 2000.

Table 1.2: FSP Model in Levels

Two Stage Least Squares Results		
$Capital_{i,t}$	0.430	***
	(0.025)	
$INF_{i,t}*Capital_{i,t}$	1.627	
	(1.509)	
$Labor_{i,t}$	0.520	***
	(0.037)	
$HEALTH_{i,t}*Labor_{i,t}$	0.001	***
	(0.0003)	
$Human\ Capital_{i,t}$	-0.188	***
	(0.045)	
$RDA_{i,t-15}*Human\ Cap_{i,t}$	0.134	***
	(0.021)	
A	5.394	***
	(0.352)	
Obs:	435	
Adjusted R^2	0.9505	

*** p<0.01, ** p<0.05, * p<0.1
Hausmann p-value < 0.0001

Table 2 shows the results of a 2SLS IV estimation of the FSP model in equation (8). First stage summaries are found in Table 3. A Hausmann test was performed to determine whether instrumentation was necessary.

This test, which is built upon the assumption that the instruments used were valid, was rejected with a p-value < 0.0001, indicating that instrumentation was, in fact, necessary.

Table 1.3: First Stage Results for Levels and Growth Models

First Stage Results in Levels						
			Dependent Variables			
	Capital	INF	Labor	HEALTH	Human Capital	
R^2	0.2069	0.6230	0.5281	0.8030	0.3738	

First Stage Results in Growth Rates						
			Dependent Variables			
	%Δk	%ΔEK	%Δl	%ΔEL	%Δh	%ΔEH
R^2	0.1045	0.1986	0.3595	0.1831	0.4644	0.2111

Table 3 shows the fit of the first stage results for estimating equations (8) and (9).

Table 1.4: Davidson and MacKinnon Test of TFP and FSP Models in Levels

Test of Hypothesis that Model B adds to Model A				Test of Hypothesis that Model A adds to Model B			
First Regression		Second Regression		First Regression		Second Regression	
$INF_{i,t}$	175.988	$\hat{y}_A$	**-0.269**	$INF_{i,t}$*$Capital_{i,t}$	-17.206 ***	$\hat{y}_B$	**0.628 *** **
	(150.285)		**(0.221)**		(2.062)		**(0.184)**
$RDA_{i,t-15}$	3.027 **	A	12.071 ***	$RDA_{i,t-15}$*Hum. $Cap_{i,t}$	0.357 ***	A	0.855 *
	(1.279)		(5.500)		(0.029)		(0.465)
$HEALTH_{i,t}$	0.072 ***	$Capital_{i,t}$	0.430 ***	$HEALTH_{i,t}$*$Labor_{i,t}$	4.284 ***	$Capital_{i,t}$	0.431 ***
	(0.013)		(0.025)		(0.006)		(0.025)
Const.	16.910 ***	$INF_{i,t}$*$Capital_{i,t}$	3.106	Const.	13.263 ***	$Labor_{i,t}$	0.357 ***
	(1.098)		(1.936)		(0.275)		(0.086)
		$Labor_{i,t}$	0.423 ***			Hum. $Capital_{i,t}$	-0.267 ***
			(0.088)				(0.073)
		$HEALTH_{i,t}$*$Labor_{i,t}$	0.003 **			$INF_{i,t}$	338.425 ***
			(0.001)				(88.966)
		Human $Capital_{i,t}$	-0.228 ***			$HEALTH_{i,t}$	-0.035 *
			(0.056)				(0.016)
		$RDA_{i,t-15}$*Hum. $Cap_{i,t}$	0.181 ***			$RDA_{i,t-15}$	-1.576
			(0.043)				(1.179)
Obs:	435		435		435		435
Adjusted R^2	0.3330		0.9505		0.8541		0.9508

*** p<0.01, ** p<0.05, * p<0.1

Table 4 shows the results of the Davidson and MacKinnon J-test. All equations are estimated via 2SLS. The significant coefficient on $\hat{y}_B$ but not on $\hat{y}_A$ indicates that model B is preferred to model A in terms of explanatory power.

Table 1.5: FSP Model Estimated over OECD and NON-OECD Subsamples

	OECD	NON-OECD
Capital	0.573 ***	0.419 ***
	(0.056)	(0.029)
INF*Capital	2.872 **	-13.576
	(1.312)	(16.917)
Labor	0.456 ***	0.527 ***
	(0.069)	(0.052)
HEALTH*Labor	0.00005	0.0018 ***
	(0.00007)	(0.0006)
Human Capital	-0.120	-0.233 ***
	(0.073)	(0.059)
RDA*Human Cap.	0.058 **	0.163 ***
	(0.027)	(0.028)
A	3.635 ***	5.492 ***
	(0.752)	(0.436)
Obs:	130	305
Adjusted R^2	0.9808	0.9100

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Hausmann p-value:	< 0.0001	< 0.0001

Table 5 shows the results of a 2SLS IV estimation of equation (8) over two samples, OECD countries and NON OECD countries. A pair of Hausmann tests were performed to determine whether instrumentation was necessary.

These tests, which are built upon the assumption that the instruments used were valid, were each rejected with a p-value < 0.0001, indicating that instrumentation was, in fact, necessary.

Table 1.6: FSP Model in Growth Rates

	Two Stage Least Squares Results
%Δk	0.011
	(0.049)
%ΔEK	2.930 *
	(1.696)
%Δl	0.355 **
	(0.177)
%ΔEL	0.001 ***
	(0.0003)
%Δh	-0.179 ***
	(0.060)
%ΔEH	0.061 ***
	(0.018)
Obs:	347
Adjusted R^2	0.2032

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Hausmann p-value < 0.0001

Table 6 shows the results of a 2SLS IV estimation of equation (9). A Hausmann test was performed to determine whether instrumentation was necessary.
This test, which is built upon the assumption that the instruments used were valid, was rejected with a p-value < 0.0001, indicating that instrumentation was, in fact, necessary.

Table 1.7: Davidson and MacKinnon Test of TFP and FSP Models in Growth Rates

Test of Hypothesis that Model B adds to Model A				Test of Hypothesis that Model A adds to Model B			
First Regression		Second Regression		First Regression		Second Regression	
$\%\Delta INF_{i,t}$	0.141 (0.107)	$\hat{y}_A$	**1.016** *** **(0.069)**	$\%\Delta EK$	-0.605 (1.270)	$\hat{y}_B$	**0.908** *** **(0.101)**
$\%\Delta RDA_{i,t-15}$	0.261 (0.219)	$\%\Delta k$	0.012 (0.039)	$\%\Delta EH$	0.005 (0.012)	$\%\Delta k$	0.008 (0.037)
$\%\Delta HEALTH_{i,t}$	0.201 (0.197)	$\%\Delta EK$	-0.366 (1.343)	$\%\Delta EL$	0.0001 (0.0002)	$\%\Delta l$	-0.002 (0.127)
Const.	0.122 *** (0.014)	$\%\Delta l$	0.003 (0.140)	Const.	0.140 *** (0.009)	$\%\Delta h$	-0.046 (0.045)
		$\%\Delta EL$	-0.00001 (0.0002)			$\%\Delta INF$	0.116 (0.109)
		$\%\Delta h$	-0.041 (0.048)			$\%\Delta HEALTH$	0.121 (0.224)
		$\%\Delta EH$	0.0006 (0.014)			$\%\Delta RDA$	0.212 (0.223)
Obs:	347		347		347		347
R^2	0.0116		0.5139		0.0023		0.5236

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7 shows the results of the Davidson and MacKinnon J test for the growth model. All equations are estimated via 2SLS. The significant coefficients on $\hat{y}_B$ and on $\hat{y}_A$ indicate that both models have unique contributions in terms of explanatory power.

Table 1.8: Factor Accumulation Regressions in Levels and Growth Rates

	Levels Regressions				Growth Regressions		
	Dependent Variable:				Dependent Variable:		
	$k_{i,t}$	$h_{i,t}$	$l_{i,t}$		$\%\Delta k_{i,t}$	$\%\Delta h_{i,t}$	$\%\Delta l_{i,t}$
$INF_{i,t-5}$	38.608	-66.816	-94.488	$\%\Delta INF_{i,t-5}$	0.169 ***	0.128 ***	0.083 ***
	(101.385)	(100.194)	(98.953)		(0.038)	(0.049)	(0.030)
$HEALTH_{i,t-5}$	0.108 ***	0.042 ***	-0.002	$\%\Delta HEALTH_{i,t-5}$	1.415 ***	2.459 ***	1.530 ***
	(0.012)	(0.012)	(0.012)		(0.265)	(0.341)	(0.204)
$RDA_{i,t-15}$	4.126 ***	1.940	1.909	$\%\Delta RDA_{i,t-15}$	0.725 ***	1.012 ***	0.632 ***
	(1.326)	(1.310)	(1.294)		(0.274)	(0.352)	(0.211)
Constant	14.466 ***	12.353 ***	13.508 ***				
	(1.008)	(0.996)	(0.983)				
Obs:	347	347	347		259	259	259
Adjusted R^2	0.4940	0.1182	0.0004		0.2679	0.2951	0.3151

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8 shows the results of estimating equations (11)-(16).

Chapter 2: Growing at Your Neighbor's Expense? A spatial examination of growth in the Americas

2.1 Introduction

In a global environment where the economies and experiences of countries are increasingly shared and interdependent, it seems logical that the growth experience of one country might be importantly related to the growth experience of other countries, especially those other countries with which the first country is most economically intertwined. Still, most models of economic growth look at countries in isolation, ignoring any of the potential spatial effects of growth (or lack of growth) from neighboring countries. Understanding the interactions and relationships between the growth experiences of different countries could enlighten policymakers about how to achieve consistent, stable growth.

Spatial growth spillovers could have strong policy implications for developed and developing countries alike. If spatial effects are positive, coordinated efforts among neighbors might be able to jumpstart growth for an entire region. Given the existence of growth spillovers, the best way to create growth in a region may be to target one or two specific countries for aid or intervention and to allow the resulting effects to spread through spatial channels. On the other hand, if net spatial effects are negative, policymakers would want to find ways to circumvent these spillover effects, in which case understanding the spatial effects might be even more important. The existence of un-modeled spillovers, either positive or negative, could also lead to biased estimation of the impacts of the myriad programs targeting growth.

Using a panel of countries in continental North, Central, and South America over a thirty year period, this paper estimates a Spatial Durbin Model of the growth process, finding evidence of statistically significant negative growth spillovers. These results are robust to other spatial weighting schemes and to changes in the spatial model used. Using the estimated spatial effects from the preferred model, the dollar value of net spillovers from a growth shock in one country is economically significant as well as statistically significant.

This paper contributes to the limited literature on spatial models of international growth by focusing on and incorporating three ways in which basic spatial models have been improved. However, these improvements have not yet become common in the literature. First, few spatial models of international growth engage in any clear, empirical model selection procedure. This paper follows the approaches of Elhorst (2010) and LeSage and Pace (2009) to determine the appropriate spatial model. A second area of potential improvement is a shift away from the use of panels which contain countries from all over the globe but have only limited coverage in most regions. Spatial effects are likely to be localized, making a global focus questionable, and shocks which are common to groups of countries within a region may be heterogeneous across regions and difficult to account for using global time fixed effects. By focusing on only a single region (the continental Americas) and having almost complete coverage, these issues are not a concern in this study. The third improvement is appropriately distinguishing between common shocks to countries in the panel and growth spillovers. Failure to account for common shocks leads to an upward bias in estimates of spatial relationships. The standard panel data approach to dealing with common shocks is to include time-period fixed effects. Few spatial models of international growth have done this, in part because the inclusion of fixed effects in spatial models leads to biased estimates of model parameters. This paper includes time period fixed effects, but also employs the bias correction procedure of Lee and Yu (2010).

The rest of this paper is structured as follows. Section II introduces the most common spatial models and reviews the existing literature on spatial models of international growth. Section III discusses the spatial model selection process and the data which is used in the empirical analysis. Section IV presents the results of the empirical estimation and checks the robustness of results to alternative models and alternative spatial weighting matrices. Section V discusses the real economic value of spatial growth effects and provides an example of how these effects could bias policy evaluation if not properly modeled. Section VI returns to the existing literature on growth spillovers to examine how previous results are affected when a model takes into account the suggestions of this paper. Section VII suggests future directions of research and concludes.

2.2 The Direction of Growth Spillovers, Common Spatial Models, and Existing Literature

2.2.1 The Direction of Spillovers

A casual inspection of international growth rates suggests that spatial correlations among growth rates are positive. Countries in North America and Western Europe have typically experienced positive growth rates. At the same time, Sub-

Saharan African countries have almost universally performed less well. It is easy to assume that these positive correlations across countries' growth rates are due to positive spillovers of growth. However, theories about how spillovers operate do not unambiguously suggest that spillovers would be positive. Consider trade as a channel for potential spillovers. Growth in A might lead to increased trade between A and B. Frankel and Romer (1999) suggest that this would in turn lead to growth in B, a positive spillover. On the other hand, another plausible story is that growth in A might make A's goods cheaper in international markets, causing reduced growth in A's competitor, country C (a negative spillover).

As another example, consider a model where country leaders learn by watching policy outcomes of their neighbors. If country A implements a policy which seems to generate positive growth, neighboring country B might choose to emulate the policy, growing as well (a positive spillover). Alternatively, country A could just as easily implement a policy which might hinder growth. Country B, observing this, might avoid similar policies, or even choose opposing ones, leading to a better outcome (a negative spillover). With ambiguity about the theoretically predicted direction of spillovers, solid empirical evidence is essential.

There are multiple potential channels for spatial growth effects, and many of these channels might suggest that spillovers could be negative, e.g., channels where countries are in competition with each other. The lack of a conclusive theoretical prediction about the direction of these effects highlights the need for empirical investigations of the issue. The next section will introduce the most common models used to investigate spatial effects and will examine several attempts in the existing literature to identify and quantify spatial growth effects across countries.

2.2.2 Common Spatial Models

For a more thorough and in-depth description of spatial modeling, the reader should refer to Anselin, Le Gallo, and Jayet (2008) or LeSage and Pace (2009). The following is simply a brief overview of the most common spatial models. Three of the most common panel spatial models all stem from a standard panel regression form, as in (2.1).

$$y_{i,t} = x_{i,t}\beta + \mu_{i,t} \tag{2.1}$$

Here, x is a vector of k explanatory variables and $\mu_{i,t}$ is independently distributed $N(0, \sigma^2)$. The first spatial model relaxes the assumption that the error terms are independently distributed. Instead, it is assumed that there is some correlation of the error terms across space according to (2.2).

$$\mu_{i,t} = \lambda \sum_{j=1}^{N} w_{i,j}\, \mu_{j,t} + \varepsilon_{i,t} \tag{2.2}$$

The parameter $w_{i,j}$ is the row i, column j element of the matrix W, which is known as a spatial weight matrix. This matrix describes the level of "relatedness" across the sample of observations. The choice of a spatial weighting matrix is up to the researcher, but common forms reflect physical distance between observations or physical contiguity of particular observations, with zeros along the diagonal. The λ term captures the extent to which shocks to one country spill over to another country, given their level of relatedness. The model resulting from a combination of (2.1) and (2.2) is known as the Spatial Error Model (SEM). The SEM is appropriate when it is believed that the correlation across dependent observations results from spatial correlation in the shocks to the data generating process.

The second common spatial model expands upon (2.1) to allow for a direct spatial relationship among dependent variable observations. The model does so by including a spatially weighted vector of the dependent variable as an explanatory term. The resulting model is known as the Spatial Autoregressive (SAR) model or the Spatial Lag model.

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j} y_{i,j} + x_{i,t}\beta + \mu_{i,t} \tag{2.3}$$

In this case, neighboring values of the dependent variable are weighted according to a spatial weighting matrix. The SAR model is appropriate when it is believed that the spatial dependence is inherent in the dependent variable.

A third common model of spatial dependence is the Spatial Durbin Model (SDM). The SDM expands upon the SAR model in (2.3) by allowing for a spatial relationship not only in the dependent variable, y, but also in the independent variables, x. The inclusion of this additional term results in the specification in (2.4).

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j} y_{j,t} + x_{i,t}\beta + \sum_{j=1}^{N} w_{i,j} x_{j,t}\gamma + \mu_{i,t} \tag{2.4}$$

Here, both β and γ are k $\times$ 1 vectors of parameters. Both the SEM and SAR models can be viewed as special cases of the SDM given appropriate restrictions on parameters.

As with non-spatial panel models, the SER, SAR, and SDM panel models can be augmented with time and/or spatial fixed effects. Time fixed effects are of particular interest in spatial models because the existence of common, un-modeled shocks across time lead to an upward bias in the estimates of the spatial parameters of interest. Lee and Yu (2010) point out that time fixed effects may be especially important in growth theory.

The process for model selection among these three candidates will be addressed in section IV. Prior to that, the next subsection examines the existing spatial literature on international growth, focusing on the each paper's choice of countries used in the sample, the model used in estimation along with model selection process, and the choice to include or omit time fixed effects in estimation.

2.2.3 A Review of the Literature on Growth Spillovers

Only a very limited number of other papers have examined international growth spillovers, but within this literature one can observe a variety of different models, estimated over different time periods, and using different data. However, the existing literature almost always finds evidence of positive growth spillovers among countries.

Of the papers on international spatial growth effects, three look exclusively at a spatially autoregressive process, as in (2.3). Easterly and Levine (1997), one of the earliest and best known works allowing for spillovers, studies the African growth experience in an SAR framework without fixed effects and find evidence of positive spatial effects across countries. From their results, they conclude that policy changes which affect growth are more powerful when coordinated with policy changes in neighboring countries.

Behar (2008), also using an SAR model, finds evidence of positive spatial effects in a global panel. Spatial effects are found to be strongest in smaller regions and weaker in larger regions or globally. Time fixed effects are included in the global models, but Behar points out that it is difficult to distinguish between spillovers and common shocks in his specification.

Roberts and Deichman (2009) also use an SAR model to look at long-run spatial growth effects, focusing on how these effects may be heterogeneous across a global sample of countries and how this heterogeneity may be systematically related to infrastructure. They find that positive spatial effects are magnified by higher levels of transportation and communication infrastructure. They highlight, additionally, the diminishing effects of low transportation infrastructure and being landlocked on spatial effects. The SAR model used includes country fixed effects, but because they use long-run growth rates, they only have a single cross section of average growth rates so they do not include time fixed-effects.

In addition to the three aforementioned papers which utilize only an SAR framework to examine spatial growth effects internationally, three additional papers examine these effects using a combination of models. Both Moreno and Trehan (1997) and Abreu, de Groot, and Florax (2004) examine spatial growth effects using a combination of SAR and SEM models. Moreno and Trehan find positive spatial effects on a global sample of countries using their SAR model, and then find further evidence of common "shocks" to countries in an SEM framework. Abreu, de Groot, and Florax use both models to test for spatial effects and spillovers on Total Factor Productivity across countries, again finding evidence of positive effects in their global sample. Weinhold (2002) applies an SAR model of spatial growth effects to a global sample. She finds positive spatial effects in her model, which includes country and time fixed effects. Weinhold then extends her model to a limited SDM model where one of her explanatory variables (a TFP residual) also has a spatial effect on other countries. Weinhold is somewhat different from other works, in that her models only allow for spatial effects among either developed or developing countries. Her results indicate the existence of positive spatial growth effects.

A final paper uses tests for spatial model selection to choose the appropriate spatial framework for analyzing spatial growth effects. Ertur and Koch (2005) extend the Augmented Solow Model of Mankiw, Romer, and Weil (1992) to a spatial setting. Their tests indicate that the data is best represented by a Spatial Durbin Model. The resulting estimates of spatial growth effects are positive in a model including neither country nor time fixed effects, again estimated on a global sample.

Section III moves on to a full discussion of the model employed here. After introducing the data, the model selection procedure will be discussed along with its results. Special attention is given to the importance of choices regarding the inclusion of fixed effects. Lastly, the estimation approach of the selected spatial model will be outlined.

2.3 Data, Model Selection, and Estimation

2.3.1 Growth and Growth Spillovers

The economies of groups of countries are interrelated in a variety of ways and to differing degrees. Examining the different pathways in which spatial effects may be transmitted provides insights into the potential importance of these effects as well as into the ability of policymakers to manipulate, magnify, or avoid spatial effects on growth.

For the purposes of this paper, growth (positive or negative) will refer to the year over year percentage changes in per-capita GDP in a country, while "growth spillovers" will be the net spatial effects of growth in one country on other countries, regardless of the source of the initial growth. It is important to distinguish between two scenarios. The first is one in which a change in country A's growth causes a change in country B's growth. A scenario like this is the type of growth spillover which this paper focuses on, and would be captured by the ρ parameter in an SAR model or an SDM. The second scenario is one in which a change in some other variable in country A, like a war, leads to simultaneous changes in growth in both country A and country B. This type of effect is what would be captured by the γ parameter in an SDM framework. While it may be important to control for this second type of scenario, because the initial shock was not in country A's growth, this is not the primary effect of interest here.

2.3.2 The Data

To reiterate, the goal of this paper is to identify any spatial effects of the growth of one country on its relevant neighbors, regardless of the source of the initial growth. To isolate any such effects, the model includes a set of variables in the X vector intended to control for other common sources of growth variations. In this paper, the vector of control variables will consist of physical capital growth rates, changes in terms of trade, and an indicator of war within a country's borders.

Like Easterly and Levine, who focused exclusively on Africa, I examine spatial growth effects within a single, clearly defined region: the continental Americas. This provides several advantages over more global models. First, I have almost universal data coverage for the sovereign states in the region. From the 22 nations in the continental Americas, I form a 29 year panel including 19 countries (The three omitted countries are Belize, Guyana, and Suriname). The second benefit of focusing on a single geographical region is that spillovers should be most pronounced within this region. The continental Americas are geographically isolated from other areas, and a large percentage of trade from these countries is within region as well (approximately 20% over the sample period according to the IMF's DOTS). The third benefit is that, as was pointed out by Roberts and Deichman, spillovers may be heterogeneous across regions, so looking across multiple regions at once may muddle estimates.

Data on GDP growth and capital stock growth rates come from the Penn World Tables. Capital stock growth rates are calculated from the investment series using a perpetual inventory method with an assumed five percent depreciation rate. Terms of trade data are from the World Development Indicators, and the war indicator represents the sum of civil and international indicators for political violence from the Major Episodes of Political Violence dataset maintained by Monty Marshall at the Center for Systemic Peace. Table 2.1 provides summary statistics for these variables. All data are collected for the 19 countries in the continental Americas which have complete coverage during the 30 year period from 1978-2007.

2.3.3 The Spatial Weight Matrix

All of the potential spatial models require that a spatial weight matrix be chosen. An appropriate spatial weight matrix reflects the level of "relatedness" of all observations in the sample, but the exact form of the matrix is up to the researcher. Initially, a common form of this matrix reflecting the physical distance between spatial units will be used here. In a later section, the robustness of results to alternative specifications of this matrix will be examined as well.

The precise form of the primary weighting matrix is as follows. The diagonal elements of the weighting matrix are all zero. Geographic distance is defined as the straight-line distance between the centers of countries. Because nearer countries are hypothesized to have stronger spillovers, the geographic distance is inverted so that larger values correspond to closer countries. Because spillovers create feedback loops (where growth from A spills over to B, but then this growth change in B spills back to A and so on), an infinite series of spatially weighted growth effects is created. To guarantee convergence of this series, which is necessary for the model estimation process, each row of the spatial weighting matrix must be normalized so that the entries sum to one[4].

Earlier works, like Easterly and Levine (1997), used more basic weighting matrices which treated all countries as potential neighbors, but re-weighted the observations by country size. While the intuitive power of such a weighting scheme is clear, it lacks the mathematical properties necessary to ensure convergence.

2.3.4 Model Selection

The model selection process, proposed in Elhorst (2010), begins with a test of whether spatial effects are even appropriate. The non-spatial model is compared to SAR and SEM alternatives with Lagrange multiplier tests. A test of a hypothesis that this paper's data exhibits no spatial lag is rejected with a p-value of 0.018. A test of the hypothesis that the data exhibits no spatial error is also rejected, with a p-value of 0.008. Given that these tests indicate that both spatial models are preferred to the non-spatial alternative, the selection process then involves estimation of a Spatial Durbin Model, which can be viewed as the most general of the three spatial models discussed. The SAR model in (2.3) can easily be seen as a special case of the SDM where $\gamma=0$. The SEM model is a special case of the SDM as well, the case where $\gamma+\rho\beta=0$ (Burridge, 1981). Testing these two hypotheses via likelihood ratio tests is then an appropriate method of choosing among the three models. If the two hypotheses are rejected, the SDM model is the most appropriate. If the first hypothesis cannot be rejected, the appropriate model is the SAR, and if the second hypothesis cannot be rejected, the SEM

[4] Matrices of this particular form have also been used by Roberts and Deichman, Moreno and Trehan, Abreu, de Groot and Florax, Ertur and Koch, and Weinhold.

model is appropriate. If these hypothesis tests do not point conclusively to either the SAR or the SEM model, the more general SDM model is deemed appropriate.

A likelihood ratio test comparing the SDM and SAR model is unable to reject the hypothesis that the SDM can be reduced, and that the SAR is appropriate (p-value of 0.308). Similarly, a likelihood ratio test of the hypothesis that the SDM can be reduced to an SEM cannot be rejected (p-value of 0.247). Following Elhorst (2010), when these tests fail to indicate that only one of the more simple models is appropriate, the general SDM is the appropriate choice[5].

2.4 Model Estimation and Empirical Results

Having settled on a Spatial Durbin Model, the expression in (2.4), can be modified to include time and/or spatial (country) fixed effects:

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j} y_{j,t} + x_{i,t}\beta + \sum_{j=1}^{N} w_{i,j} x_{j,t}\gamma + \theta_i + \tau_t + \mu_{i,t} \qquad (2.5)$$

The inclusion of the Wy term on the right hand side of the equation introduces simultaneity issues, making the use of OLS inappropriate for estimation. However, the dependent variable can algebraically be solved for in matrix notation as:

[5] Each individual test fails to reject a hypothesis that the general model can be simplified to a simpler one. Given these results that either simpler model may still be appropriate, it seems somewhat clumsy that the approach says to stick with the general model. One could instead argue that a much larger rejection region is appropriate for these tests if neither test is able to reject the null at standard levels, even a rejection region as large as 0.4 or 0.5. In that case, both tests indicate that the SDM is more likely than the simpler alternatives.

$$Y = (I - \rho W)^{-1}(X_i\beta + WX\gamma + \theta_i + \tau_t) \; + \; (I - \rho W)^{-1}\mu \qquad (2.6)$$

Under the assumed classical structure of the underlying error term μ, equation (2.6) can then be estimated via maximum likelihood.

Lee and Yu (2010) discuss how standard estimation of any spatial model which contains spatial and/or time fixed effects, like the model expressed in (2.5), will lead to biased estimates of some model parameters. They propose correction procedures for eliminating these biases, which are of particular importance when the breadth and/or length of the sample are small. In the case of spatial models with spatial fixed effects, but not time fixed effects, the estimate $\hat{\sigma}^2$ will be biased downward and needs to be corrected by a factor of $\frac{T}{T-1}$. In the case of spatial models with time fixed effects but not spatial fixed effects, the estimate of $\hat{\sigma}^2$ needs to be corrected by a factor of $\frac{N}{N-1}$. In the case of a spatial model with both time and spatial fixed effects, all parameter estimates are biased. The correction procedure in a model with both types of fixed effects is significantly more complex, and the reader is referred to Lee and Yu (2010) or Elhorst (2010) for a full discussion. All estimation results are reported after the implementation of the appropriate bias correction procedures.

2.4.1 Coefficient Interpretation

In a traditional non-spatial model (as in (2.1)), the partial derivative $\frac{\partial y}{\partial x}$ is simply going to be the parameter β associated with x. In a Spatial Durbin Model, $\frac{\partial y}{\partial x}$ is significantly more complex, due to the feedback loops whereby a change in x in country

A not only has a primary effect on y in country A, but also potential effects on y in all other countries in the sample and then secondary effects on y in country A. LeSage and Pace (2009) outline a system for measuring the average *direct effects* of a change in x, along with the average *indirect effects* of the change. Under their system, the *direct effect* of a change in a variable represents the average effect of a change in x_i on y_i for all countries. This direct effect would be analogous in interpretation to the single parameter β associated with x in a non-spatial framework. The *indirect effect* of a change in x would be the average effect of a change in x_i on y in all other countries. For the purposes of interpreting control variables and testing their significance in the model, the relevant questions relate to the magnitude of direct and indirect effects and whether or not these effects are statistically significant, not on the magnitude or significance of the specific β or γ parameters. Therefore, all regression results will report these results instead of specific parameter estimates.

Table 2.2 reports the estimation results from a variety of spatial models. The first panel contains results from a Spatial Durbin Model with both time and spatial fixed effects. A joint significance test of the year fixed effects finds them significant with a p-value less than 0.01. Similarly, a joint test of the country fixed effects finds them significant with a p-value less than 0.01. Therefore, I adopt this specification as the preferred model. The primary parameter of interest is ρ, reflecting the spatial growth effect this paper seeks to address. In this specification, the estimate of ρ is negative and statistically significant, indicating that a positive growth shock in one country actually leads to a significant decrease in growth rates of neighboring countries. Of course, the magnitude of this negative spatial effect will be heterogeneous across neighbors, as determined by the spatial weight matrix. More intuitively, the magnitude of the shock dissipates the farther away neighbors are. As I will highlight in the next section, this negative coefficient estimate does not necessarily mean that growth is a "zero sum" game. While a growth shock in one country will, according to these estimates, lower neighboring growth rates, the spillover to any one country is much smaller than the initial shock.

The direct effect of an increase in the capital stock is positive and quite significant, as would be expected. Increased capital stocks have no significant indirect effects on neighboring growth rates. Positive terms of trade shocks do not have any direct effect on GDP growth, but do have a significant indirect effect on neighboring GDP growth. A one percent increase in a country's terms of trade would lead to an average reduction in neighboring GDP growth of approximately one tenth of a percentage point. The warscore variable is also significant in its direct effects. A one unit increase in the score for a country leads to a one third of a percentage point decrease in growth rates in the same country. While there is an estimated average decrease in neighbors' growth rates of a little more than a percent, this effect is not statistically significant.

Panels two and three from Table 2.2 highlight the relative importance of the time and spatial fixed effects in the estimation. Panel two provides results from a Spatial Durbin Model without spatial fixed effects. While the omission of the spatial fixed effects changes the magnitude of the estimated spatial growth effect, the estimated parameter is still negative and significant. Panel three, however, shows the more drastic impact of removing the time fixed effects. This change causes the primary spatial effect to have a positive and significant estimated effect. The omission of time fixed effects to account for common shocks is thus a likely explanation for the difference between the positive spatial effects found in most of the literature and the negative effects observed here.

The final panel in Table 2.2 has estimates from an SAR model with both spatial and time fixed effects. While the model selection process indicated that the SDM was preferred, the negative and significant sign on the primary spatial parameter in the corresponding SAR model indicates that the choice of model is not the driving factor in the finding of negative spatial growth effects.

LeSage and Pace (2010) point out that in a well specified spatial model, changes in the weighting scheme actually have very little effect on parameter estimates. Still, it cannot hurt to verify that the results presented here are not being driven by the choice of the spatial weight matrix. Table 2.3 provides perspective on this issue. The first panel reproduces the results from the preferred model, which uses the geographic distance between countries to weight the spatial growth effects. The second panel has results from the same Spatial Durbin Model, but this time the geographic weighting matrix is replaced by a matrix capturing the "economic distance" between countries. Following Buera et al. (2008), who discuss how countries engage in policy observation of similar neighbors, spatial growth effects should be strongest among countries which are closest in their level of development. They suggest measuring economic distance as the absolute value of the difference in the natural logs of GDPs of the countries. This creates a matrix which is decreasing in the level of economic similarity. Again, because the elements of a weighting matrix should be increasing in the strength of spillovers, this value is inverted to form the weighting matrix of economic distance. Consistent with the spatial literature, this matrix is again row-normalized before being included in regressions. The similarity of results across the panels, especially the negative and significant coefficient on the spatial parameter of interest, indicates that the findings are not being driven by the choice of weighting scheme.

2.5 The Economic Significance of Spillovers and Policy Evaluation

2.5.1 The Real Economic Value of Spillovers

Having made an argument for the existence of growth spillovers and their statistical significance, it is important to also determine their economic significance. Do these spillovers actually matter in practice? Consider a thought exercise which supposes that every country in the Americas was holding constant at their year 2000 GDPs, when an initial 2% growth shock occurs exogenously in a single country, Argentina. Table 2.4 outlines the effects of this hypothetical shock.

First, notice that the spatial growth effects magnify this initial 2% shock to be slightly more than 2%. The dollar value of this net shock to Argentina would be approximately $6.3 billion. The estimates from the preferred SDM with spatial and time fixed effects indicates that spatial growth effects would cause GDP to contract in a number of other countries by over one fifth of a percentage point. Some countries would actually see positive net spatial effects as the negative spillover from the initial Argentinean shock is outweighed by secondary positive spillovers from the resulting decreases in other neighbors' GDPs. The real value of the spatial growth effects ranges from an almost $17 billion loss in the United States to a $56 million increase in Chilean

GDP. The net absolute value of spatial growth effects is estimated to be over $20 billion. The net change in the combined GDP of all countries varies widely in an exercise such as this depending on where and in how many countries the initial shock originates.

2.5.2 Un-modeled spillovers and policy effects

While a growing literature suggests that spatial growth effects might be impacting how neighboring countries grow in relation to each other, most papers examining growth policies do not currently account for these effects. It is worthwhile to understand how the exclusion of spatial growth effects from a model might change estimates of other parameters in growth regressions. To highlight this problem, consider a counterfactual situation where all the countries in the sample are holding steady at zero growth, when the 10 member states of Mercosur (Argentina, Brazil, Paraguay and Uruguay are full members, Venezuela, Bolivia, Chile, Colombia, Ecuador, and Peru are associate members), a South American customs union, implement a policy which, before the effects of any growth spillovers, would lead to a 2% increase in growth for its member states and have no effect elsewhere. Table 2.5 shows what the estimated growth effects of this policy would be after taking into account the spatial effects estimated by the preferred Spatial Durbin Model.

While a spatial model would be able to isolate out the 2% growth effect of the policy on the 10 member states and the zero independent growth of the remaining sample, a regression which does not account for spatial effects would mis-estimate a constant growth rate of about -1.25% and a policy effect of about 3.0% increased growth. Therefore, not only does a model which omits spillover effects have a biased estimate of the policy effect in question, it also biases the estimates of the average growth rates of other nations.

2.6 Revisiting existing literature

Using a spatial model which 1) focuses on a single region and 2) includes year fixed effects, this paper finds evidence of significant negative spatial growth spillovers. However, the existing literature on growth spillovers points exclusively to the existence of positive effects. Can this difference be explained solely by these two factors? To shed some light on this question, I re-examine an existing work while incorporating the regional focus and year fixed effects. From the perspective of this paper, Behar (2008) provides an ideal starting point for this exercise. Behar's work is the best option for this type of comparison because, like this paper, he uses annual growth rates to examine short-run spillovers. Additionally, Behar employs models both with and without time dummies, but at the global level rather than regionally. Using Behar for comparison allows for evaluation of the effects of the regional focus, the effects of the yearly dummies, and the effects of the combination of both.

While Behar uses a variety of models which allow for spillovers at the neighborhood level, the regional level, and the global level, his starting point is a basic SAR model of the form:

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j} y_{i,j} + \mu_{i,t} \tag{2.7}$$

This model is estimated for 134 countries for up to 25 years. The spatial weighting matrix assigns a value of 1 for every pair of countries within 1000 km of each other, as measured by the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). This model is reproduced over the same time period for the 76 countries for which complete data could be found. Behar's results, along with the results of the replication exercise, can be found in Table 2.6.

Comparing the Behar results in panel 1 with the replicated results in panel 2, the sign and significance of the estimated spillovers is preserved in the replication exercise. The same can be said comparing panels 4 and 5, which are Behar's results from a model adding in a regional spillover and this model's respective replication. The similarities of the replicated results to their counterparts imply that sample differences do not seem to be creating vastly different parameter estimates. Panels 3 and 6 of Table 2.6 examine how Behar's model behaves when spillover effects are the same across regions, but each region is allowed to have its own yearly fixed effects. Panel 3, corresponding to Behar's model with only neighborhood spillovers, has a much smaller estimated spatial effect. In fact, the spatial effect is no longer statistically significant, with a p-value of 0.968. Panel 6, corresponding to Behar's model with both neighborhood and regional effects, again has a much smaller estimated neighborhood spillover which is statistically indistinguishable from zero (p-value of 0.891), while the estimated regional spillover becomes negative and highly significant. The absence of the yearly fixed effects seems to be responsible for an upward bias of the spillover coefficient, as would be predicted. Moreover, the inclusion of a universal yearly fixed effect in the model was not sufficient to account for the shocks which seem to have effects which are better modeled at the regional level. As long as shocks occur at a regional level, the inclusion of year fixed effects in a model extending beyond the region will not be able to properly account for shocks and they will instead continue to create an upward bias in spillover estimates.

2.7 Conclusion

While spatial growth models are well established at sub-national levels, there has been much less investigation of growth spillovers internationally. International models which do examine spatial growth effects often fail to include time fixed effects or, if they do include time fixed effects, these models may use global samples instead of focusing on specific regions where common temporal shocks are harder to capture. Together, these two factors may lead to upward biases in estimates of spatial growth effects. This paper adds to the spatial growth literature by estimating a carefully selected spatial model over a clearly defined sample of countries. When time fixed effects are included in this model, estimate spatial growth effects are actually negative and significant. These effects are robust to choices of spatial weighting matrix and to alternative spatial models. Moreover, the economic importance of spatial growth effects is demonstrated as well. Failure to properly include spatial growth effects in growth models then leads to incorrect estimates of policy effects in growth models. Further research will be required to see if growth spillovers may be universally negative, or if this phenomenon is only true within certain regions. Recognizing the existence of negative spatial growth effects, while not ideal for helping groups of countries to develop, is still important to understanding how best to accomplish this goal. Determining if these effects are due to the competitive role of countries in international trade or due to other factors is an important direction for future research.

Table 2.1
Summary Stats

Variable	Obs	Mean	Std. Dev.	Min	Max
$\%\Delta y_{i,t}$	551	1.02	4.96	-41.11	35.91
$\%\Delta k$	551	2.21	2.62	-9.1	11.93
$\%\Delta ToT$	551	0.86	12.47	-46.65	97.61
Warscore	551	0.78	1.64	0	6

Table 1 provides summary statistics for the growth rates of the countries in the sample and the three control variables used in the regressions.

Table 2.2

		Spatial Durbin Model with Time and Spatial Fixed Effects	Spatial Durbin Model with only Time Fixed Effects	Spatial Durbin Model without Fixed Effects	Spatial Autoregressive Model with Time and Spatial Fixed Effects
	Weighted Neighbors' Growth	-0.54 ***	-0.92 ***	0.30 ***	-0.55 ***
		(-3.65)	(-6.33)	(3.21)	(-3.83)
Direct Effects	%Δk	0.86 ***	0.80 ***	0.77 ***	0.82 ***
		(8.50)	(9.79)	(9.96)	(8.65)
	%ΔToT	0.02	0.02	0.03 *	0.02
		(0.95)	(1.02)	(1.68)	(1.47)
	Warscore	-0.34 *	-0.21 *	-0.27 **	-0.22
		(-1.73)	(-1.75)	(-2.42)	(-1.23)
Indirect Effects	%Δk	0.10	0.10	-0.01	-0.28 ***
		(0.21)	(0.30)	(-0.07)	(-4.84)
	%ΔToT	-0.11	-0.09	-0.06	-0.01
		(-1.34)	(-1.32)	(-0.91)	(-1.39)
	Warscore	-1.23	0.08	-0.60	0.08
		(-1.52)	(0.17)	(-1.42)	(1.19)
	R-squared:	0.370	0.364	0.220	0.363
	Obs:	570	570	570	570

Table 2 provides a series of regression results. The dependent variable in all specifications is GDP growth. T-stats are in parentheses.
Panel 1 has results from the preferred specification, an SDM model with both time and spatial fixed effects.

Panel 2 allows for comparison with a model which omits the spatial fixed effects. This omission doesn't substantively alter results.
Panel 3 allows for a comparison with a model which no longer has time fixed effects. This change causes the estimate of the primary spatial effect to change sign.

Panel 4 allows for comparison between an SDM model and an SAR model.

* p-value <0.1   **p-value<0.05   ***p-value<0.01

Table 2.3

		SDM with both fixed effects, Geographic Distance Weighting		SDM with both fixed effects, Economic Distance Weighting	
	Weighted Neighbors' Growth	-0.54	***	-0.33	***
		(-3.65)		(-2.79)	
Direct Effects	%Δk	0.86	***	0.82	***
		(8.50)		(8.32)	
	%ΔToT	0.02		0.03	*
		(0.95)		(1.78)	
	Warscore	-0.34	*	-0.23	
		(-1.73)		(-1.21)	
Indirect Effects	%Δk	0.10		-0.17	
		(0.21)		(0.22)	
	%ΔToT	-0.11		0.05	
		(-1.34)		(0.51)	
	Warscore	-1.23		-0.67	
		(-1.52)		(-0.71)	
	R-squared:	0.370		0.347	
	Obs:	570		570	

Table 2 provides a comparison of regressions with different spatial weight matrices. The dependent variable in all specifications is GDP growth. T-stats are in parentheses.
Panel 1 is the preferred specification using a geographic weighting matrix. Panel 2 uses an economic distance weighting matrix instead.

* p-value <0.1 **p-value<0.05 ***p-value<0.01

Table 2.4

		New Growth Rate	Value of Spatial Growth Effect (millions of $)
Spillovers to:	**Argentina**	2.07%	6,290
	Bolivia	0.01%	2
	Brazil	-0.02%	-242
	Canada	-0.14%	-1,244
	Chile	0.05%	56
	Colombia	-0.13%	-252
	Costa Rica	-0.20%	-65
	Ecuador	-0.11%	-58
	El Salvador	-0.21%	-59
	Guatemala	-0.20%	-108
	Honduras	-0.21%	-37
	Mexico	-0.17%	-1,568
	Nicaragua	-0.21%	-20
	Panama	-0.18%	-30
	Paraguay	0.04%	7
	Peru	-0.05%	-55
	United States	-0.17%	-16,600
	Uruguay	0.05%	12
	Venezuela	-0.13%	-183
	Initial Shock Value:		6,290
	Net Absolute Spillovers to other nations:		20,598

Table 4 shows the total growth rate effects, along with their dollar value, from a hypothetical 2% growth shock to Argentinean growth. These values are calculated using the parameter estimates from Table 2, panel 1.

Table 2.5

		Initial Growth	Net Growth Rate
Spillovers to:	**Argentina**	2%	1.95%
	Bolivia	2%	1.97%
	Brazil	2%	1.87%
	Canada	0%	-1.12%
	Chile	2%	1.93%
	Colombia	2%	1.38%
	Costa Rica	0%	-1.20%
	Ecuador	2%	1.49%
	El Salvador	0%	-1.35%
	Guatemala	0%	-1.36%
	Honduras	0%	-1.35%
	Mexico	0%	-1.28%
	Nicaragua	0%	-1.31%
	Panama	0%	-1.06%
	Paraguay	2%	1.99%
	Peru	2%	1.72%
	United States	0%	-1.26%
	Uruguay	2%	1.95%
	Venezuela	2%	1.37%

Table 5 shows the post-spillover growth rates of the countries in the sample from a hypothetical exercise where the Merosur countries are assumed to each experience a pre-spillover 2% growth shock.

Table 2.6

	Behar's Results (Table 2, Panel 1)	Replication of Behar (Table 2, Panel 1) on modified sample	Replication of Behar (Table 2, Panel 1) with region specific year FE	Behar's Results (Table 2, Panel 5)	Replication of Behar (Table 2, Panel 5) on modified sample	Replication of Behar (Table 2, Panel 5) with region specific year FE
Weighted Neighbors' Growth Rate	0.111 ***	0.281 ***	0.002	0.068 ***	0.161 ***	0.007
Regional Growth Rate				0.189 **	0.191 *	-5.05 ***
Obs:	1390	1824	1824	1390	1824	1824
Country FE:	Yes	Yes	Yes	Yes	Yes	Yes
Yearly FE:	No	No	Region Specific	Global	Global	Region Specific

Table 6 provides results from Behar (2008), replicated versions of these results on a slightly modified sample, and replicated versions of these results when region specific yearly fixed effects are added to the models. T-statistics are not reported in Behar, and so are omitted here as well.

* p-value <0.1 **p-value<0.05 ***p-value<0.01

Chapter 3: Uncertainty is Depressing

3.1 Introduction

What are the effects of deficit uncertainty on production? It is common to hear references in the media or in press releases from investment firms about how uncertainty over the federal deficit is holding back economic growth. Attention to deficit uncertainty is only heightened when election season inevitably rolls around and candidates make promises about improving economic performance. The academic literature, however, has much less to say about the theoretical relationship between deficit uncertainty and output growth, and empirical investigations of the issue are even scarcer.

In this paper, I consider evidence from a total of eight countries with sufficient data on deficits, output, and prices. Four countries, Brazil, Korea, Mexico, and US, have sufficiently long monthly series. Seven countries, Australia, Barbados, Korea, Malaysia, Mexico, and US, have sufficiently long quarterly series. Other countries lack continuous data in at least one of the series, are cannot be included.

I develop a framework for testing the empirical effects of deficit uncertainty on output growth on a country-specific basis using a VAR GARCH-M model of inflation, deficit growth, and output growth. The conditional means and conditional variances of these variables are estimated, and the conditional standard deviations are included in the output growth equation as measures of uncertainty.

I find evidence that deficit uncertainty depresses US output growth in models using either monthly or quarterly data. Mexico also demonstrates evidence of a negative effect with monthly data, while the other two countries show no evidence of a statistically significant effect. No countries show a positive effect in the monthly data. Quarterly data results are similar. The US and Australia show evidence of a negative effect, four countries have no significant effect, and only Mexico shows evidence of a positive effect. Also of interest, all evidence of negative effects comes from OECD countries with only one OECD country (Korea) showing no effect, indicating that the phenomenon may be more likely in more developed countries.

I demonstrate the practical effects of deficit uncertainty on inflation and output growth by simulating the effects of an average-sized one-time shock to the US deficit. Such a shock leads to an increase in uncertainty which slightly lowers inflation and output growth for about 10 quarters. I also show the effects of a permanent shock to deficit uncertainty of the same size, which leads to larger, permanent decreases in inflation and output growth.

The remainder of this paper is structured as follows. In Section II I highlight popular media's discussion of deficit uncertainty and discuss the academic literatures regarding i) deficit uncertainty and ii) macroeconomic GARCH-M modeling. Section III discusses the use of conditional heteroskedasticity estimates of uncertainty. I then test the data for evidence of conditional heteroskedasticity and develop an appropriate VAR GARCH-M model for each country. Section IV presents the empirical results on the significance of the conditional heteroskedasticity parameters, the effects of uncertainty on output growth, and includes tests for any remaining heteroskedasticity. In Section V I establish and discuss estimates of the practical effects of deficit uncertainty in the United States. Section VI concludes.

3.2 Literatures on Deficit Uncertainty and GARCH-M Modeling

3.2.1 Deficit Uncertainty in the Media

Despite its understudied nature in the academic literature, it is not uncommon to see or hear references to the effects of deficit uncertainty in newspaper articles, television news programs, campaign speeches, or releases and forecasts from financial institutions. The current state of uncertainty in the US, coupled with an upcoming presidential election, has led to these references becoming abundant. Most writers and institutions, including the Associated Press and Bloomberg, among others, argue or cite that deficit and fiscal uncertainty do have depressing effects on economic growth (Hoover, 2011; Hubbard, 2011; Jordan, 2011; The Associated Press, 2011). Glenn Hubbard, in an opinion piece for Bloomberg, summarizes this point of view saying, "Uncertainty becomes the enemy."

However, not everyone agrees with this perspective. A piece from The Atlantic responding to Hubbard argues that while uncertainty about future regulation may be problematic, deficit uncertainty does not affect economic behavior or outcomes (Indiviglio, 2011). However, regardless of which side of the debate any one source espouses, it is unclear how uncertainty is being measured, how uncertainty has been included in previous models or forecasts, or how any of the effects of uncertainty may have been quantified. Understanding and quantifying these effects may, though, be of particular importance now, argue Robert Blendon and John Benson (2011), given that the current "hyper-partisan" nature of American politics is likely to create heightened levels of uncertainty for years to come.

3.2.2 Deficit Uncertainty in Academic Literature

There is little published work, theoretical or empirical, focused on the effects of deficit uncertainty on economic growth. A small, mostly overlapping literature looks at the effects of overall fiscal uncertainty on growth, without focusing exclusively on federal deficits. Rankin (1998) builds a theoretical DSGE model which demonstrates how fiscal uncertainty may decrease aggregate demand, and if prices are fixed, output as well. Hermes and Lensink (2001) argue that budget deficit uncertainty in LDCs leads to capital flight, as individuals choose to hold assets in less risky accounts abroad.

More recently, Sims (2011) used a quarterly VAR model from 1960 to 2010 including the US federal deficit to show how deficit shocks affect monetary policy, and in turn, may depress output. Although not strictly the same as uncertainty, these shocks play a similar role in his model. Two other recent papers have built medium-sized New Keynesian DSGE models which include measures of fiscal uncertainty. Born and Pfeifer (2011) and Fernandez-Villaverde et al. (2011) measure fiscal uncertainty with stochastic volatility models in order to distinguish between shocks to the system and changes in uncertainty which are independent of shocks. Both papers find fiscal uncertainty to have a negative effect on output growth in the US, although they differ on the magnitude. Fernandez-Villaverde et al., looking from 1970 to 2010, estimate that a two standard deviation shock to fiscal uncertainty leads to a 0.1-0.2% decrease in output along with an initial upward shock but eventual small decrease in inflation. Born and Pfeifer, over a sample from 1960 to 2010, estimate that a similar shock to fiscal uncertainty would only lead to an initial decrease in output of 0.025%, while inflation will temporarily increase.

3.2.3 Macroeconomic GARCH-M Models

The first model of conditional variance (ARCH) was introduced by Robert Engle in 1982 for studying inflation in the United Kingdom (Engle, 1982). Tim Bollerslev extended this model to allow variance to be conditional on past shocks and past levels of variance (GARCH) (1986). Engle's original model was extended to include a function of the conditional variance as an explanatory variable, creating the ARCH-M model in a study of risk premia (Engle, Lilien, & Robins, 1987), and the same extension was made to Bollerslev's GARCH model to form the GARCH-M model in order to study capital asset pricing (Bollerslev, Engle, & Wooldridge, 1988).

Since its development, the GARCH-M model has seen heavy use in the financial literature, and some application in empirical macroeconomics. Within macroeconomics, most applications involve either modeling inflation or jointly modeling inflation and output growth (Grier & Perry, 2000; Kontonikas, 2004; Grier & Grier, 2006), although the model has also seen applications related to exchange rates and trade (Kim, 2000; Grier & Smallwood, 2007) as well as applications to trade and budget deficits (Grier & Ye, Twin Sons of Different Mothers: The Long and Short of the Twin Deficits Debate, 2009). This paper builds upon the literature studying inflation uncertainty and output growth by adding a third variable of interest, deficit uncertainty, to the VAR. Not only will this allow for the study of the effects of deficit uncertainty on output growth, but it will also allow for an examination of how the previously noted effects of inflation on output growth change in a more expansive model including deficits.

3.3 A VAR GARCH-M model of Inflation, Deficit Growth, and Output Growth

3.3.1 Data

This paper is concerned with the relationships among deficit growth, output growth, and inflation. Data on these series come from the IMF's International Financial Statistics database. Continuous series on output, deficits, and producer prices of sufficient length for these purposes could be obtained in monthly form for 4 countries (Brazil, Korea, Mexico, and the US), while quarterly series on output, deficits, and consumer prices of sufficient length existed for 7 countries (Australia, Barbados, Jordan, Korea, Malaysia, Mexico, and the US)[6]. The deficit growth, output growth, and inflation series are constructed from the output, deficit, and price data. Oil price inflation is included as an exogenous regressor in each equation of the VAR. This data also comes from the IMF's IFS database. Deficit growth, output growth, inflation, and oil inflation data are all de-seasonalized using the US Census Bureau's X-12-ARIMA program before use. Dates of coverage for each country can be found in Table 3.1

3.3.2 Measuring Uncertainty

Evaluating the effects of uncertainty on output growth first requires a measurement of uncertainty. Two common approaches for obtaining a measurement of uncertainty are to use a moving standard deviation of the variable in question or to implement a conditional heteroskedasticity model and include the estimated

[6] While a much larger number of countries have good data on output and prices at quarterly and monthly frequencies, the inclusion of deficits in the analysis limits the sample of countries considerably.

measurement in the growth equation. This paper employs the second approach, where uncertainty is captured by a conditional heteroskedasticity model.

Conditional heteroskedasticity models have several advantages over moving standard deviation measurements of uncertainty. Grier and Smallwood (2007) list three advantages to this approach that are of importance here. First, moving standard deviation methods offer no way of determining if their movements are statistically different from zero. Second, moving standard deviation methods capture variation, but they cannot distinguish between predictable variation and unpredictable variation. Only unpredictable variation accurately reflects the idea of uncertainty. Third, moving standard deviation measures can make volatility measures show too much or too little persistence by including too many or too few lags. On the other hand, conditional heteroskedasticity models can test for the statistical significance of movements, capture only variation which is not predictable, and estimate the appropriate level of persistence in variability.

Finally, if the variables in question are characterized by conditional heteroskedasticity, OLS estimation is inefficient regardless of whether uncertainty measures are to be included or not. As I will show in the next subsection, all countries in my sample exhibit strong evidence of conditional heteroskedasticity for at least one of the variables included in the VAR, indicating that GARCH models are appropriate.

3.3.3 Testing for Conditional Heteroskedasticity and Model Selection

In order for a time-series to be used in a GARCH-M model, it must exhibit evidence of conditional heteroskedasticity. Therefore, a preliminary step in setting up the model is determining, for each country, which of the 3 series to be included in the

VAR should be described by an ARCH or GARCH process. To determine this, I first estimate a baseline VAR of the form:

$$\pi_t = \beta_0 + \sum_{i=1}^{m} \beta_i \pi_{t-i} + \sum_{j=1}^{m} \beta_{m+j} D_{t-j} + \sum_{k=1}^{m} \beta_{2m+k} Y_{t-k} + \beta_{3m+1} OIL_t + \varepsilon_t \quad (3.1)$$

$$D_t = \gamma_0 + \sum_{i=1}^{m} \gamma_i \pi_{t-i} + \sum_{j=1}^{m} \gamma_{m+j} D_{t-j} + \sum_{k=1}^{m} \gamma_{2m+k} Y_{t-k} + \gamma_{3m+1} OIL_t + u_t \quad (3.2)$$

$$Y_t = \theta_0 + \sum_{i=1}^{m} \theta_i \pi_{t-i} + \sum_{j=1}^{m} \theta_{m+j} D_{t-j} + \sum_{k=1}^{m} \theta_{2m+k} Y_{t-k} + \theta_{3m+1} OIL_t + v_t \quad (3.3)$$

Here, π_t, D_t, and Y_t represent inflation, deficit growth, and output growth respectively. The appropriate lag length, m, is set as the minimum value for which none of the residuals from the VAR show auto-correlation at standard significance levels.

After estimating this baseline, two tests are performed. First, Ljung-Box Q statistics are calculated to test for auto-correlation in the squared residuals at various lags. Second, a likelihood ratio test is calculated for the presence of an ARCH term for each series. Table 3.1 contains the results of these tests for both the quarterly and monthly datasets. Most series show strong evidence of conditional heteroskedasticity. For both inflation and output growth, 4 of the 7 quarterly series and 3 of the 4 monthly series show strong signals. For deficit growth, every series exhibits signs of conditional heteroskedasticity.

After establishing which series are characterized by conditional heteroskedasticity for each country, the appropriate full VAR GARCH-M model is estimated. This model would be characterized by equations (3.1) and (3.2) above, with equation (3.4) replacing (3.3) in the baseline specification.

$$Y_t = \theta_0 + \sum_{i=1}^{m} \theta_i \, \pi_{t-i} + \sum_{j=1}^{m} \theta_{m+j} \, D_{t-j} + \sum_{k=1}^{m} \theta_{2m+k} \, Y_{t-k} + \theta_{3m+1} OIL_t \; + \qquad (3.4)$$

$$\delta_1 \sigma_{\pi,t} + \delta_2 \sigma_{D,t} + \delta_3 \sigma_{Y,t} + v_t$$

The $\delta_1 \sigma_{\pi,t}$ and/or $\delta_3 \sigma_{Y,t}$ terms would be omitted for those countries where these series were not characterized by conditional heteroskedasticity. In all other cases, the full VAR GARCH-M model would also include the proper conditional heteroskedasticity equation from (3.5), (3.6), and (3.7) for each series i, below.

ARCH(1): $$\sigma^2{}_{i,t} = \omega_i + \alpha_{1,i} \varepsilon^2{}_{t-1} + \varepsilon_t \qquad (3.5)$$

ARCH(2): $$\sigma^2{}_{i,t} = \omega_i + \alpha_{1,i} \varepsilon^2{}_{t-1} + \alpha_{2,i} \varepsilon^2{}_{t-2} + \varepsilon_t \qquad (3.6)$$

GARCH(1,1): $$\sigma^2{}_{i,t} = \omega_i + \alpha_{1,i} \varepsilon^2{}_{t-1} + \rho_i \sigma^2{}_{t-1} + \varepsilon_t \qquad (3.7)$$

The covariance between series is assumed to follow the form: $cov(i,j) = \varphi \sigma_i \sigma_j$

While estimating a more extensive variance/covariance matrix would be preferable, it becomes prohibitively difficult in a 3 equation VAR, so this paper follows most of the literature in restricting the covariance to be a constant multiplied by the product of the standard deviations. I will now turn to a presentation of the key results from estimating the full VAR GARCH-M model for each country.

3.4 Empirical Results

I primarily wish to determine the effects of deficit uncertainty on output growth, but I also want to show how the inclusion of deficit growth and deficit uncertainty in the model change the effects of inflation uncertainty which have been previously documented in the literature. Table 3.2 presents the results relating to the uncertainty parameters of interest, along with the estimates from the conditional heteroskedasticity equations[7]. Table 3.3 contains the results of ex post tests for conditional heteroskedasticity in the residuals. None of the series shows any indication of conditional heteroskedasticity beyond that captured in the model, indicating that the conditional heteroskedasticity forms which were chosen are appropriate.

In the quarterly results from Table 3.2, I find evidence of a statistically significant negative effect of deficit uncertainty on output growth for two of the seven countries, Australia and the US. Mexico is the only country in the quarterly dataset which has a positive and significant estimate for inflation uncertainty. In the monthly data, Mexico and the US both show evidence of a negative effect of deficit uncertainty, and no countries show evidence of a positive effect. The reversal in sign for Mexico's estimates may be related to differences in the time periods of the sample. Mexico had monthly data from mid-1981 until early 2012, while quarterly data existed from mid-

[7] The coefficient estimates from the VAR portion of the model are not presented here to conserve space, but are available upon request.

1980 to late 1997. The behavior of the Mexican economy shifted strongly after the currency crisis in late 1994, and the monthly data reflects much more of this more stable, post-crisis period than the quarterly data. The effects of a deficit shock on deficit uncertainty are estimated to be persistent. For all three countries with quarterly data where deficit growth is modeled with a GARCH process, the coefficient estimate on the lagged variance term in the conditional heteroskedasticity equation is statistically significant and has a value greater than 0.7. The monthly models show lower levels of persistence in deficit shocks. This may indicate that shocks measured at monthly frequencies are viewed quite differently in terms of uncertainty than quarterly shocks.

One fact that stands out from the results is that the presence of negative effects of deficit uncertainty on output growth is, on the surface at least, potentially correlated with development. None of the non-OECD countries have any evidence of negative uncertainty effects, but the US has a negative estimated effect in both datasets, Australia has a negative effect, and the evidence from Mexico's more stable period in which it was an OECD member indicates a negative effect of uncertainty. While further research is required to determine if these results normally differ across level of development, it is clear that the results for the US are not necessarily consistent with results everywhere.

Results on the effects of inflation uncertainty on output growth are informative as well. Grier and Perry (2000) previously documented a negative effect of inflation uncertainty on output growth in the US using monthly data, and Grier and Grier (2006) demonstrated a negative effect in Mexico, again with monthly data. The results in Table 3.2 are consistent with these findings. However, outside of the US and Mexico, there is no additional evidence that inflation uncertainty affects output growth. There are at least two potential explanations for this phenomenon. First, it is possible that inflation uncertainty effects only exist for a limited subset of countries which includes the US and Mexico but does not include many of the other countries in my samples. Second, it may be that including deficits in the VAR and including deficit uncertainty in the model may explain much of what would otherwise have been seen as inflation uncertainty and reduce inflation uncertainty's effects. Again, further research might shed additional light on this issue.

The estimated effects of output uncertainty on output growth are statistically significant for most countries. Of the four countries in the monthly dataset with a conditional heteroskedasticity model for output growth, three countries have statistically significant estimated effects of output uncertainty. All four countries with monthly data have significant estimated effects. However, as was the case with deficit uncertainty, the estimated sign of these effects differs across countries. Again, this difference appears like it may be correlated with level of development. In the quarterly data, output uncertainty raises output growth in the US, while it hurts output growth in Korea and Jordan. In the monthly data, the three OECD countries all show a significant positive estimated effect of output uncertainty, while Brazil has a significant negative estimated coefficient.

Taken together, the results indicate that while the US data indicates a depressing effect of deficit uncertainty on output growth, this finding does not seem to apply to all countries, and may only exist for some developed countries. Inflation uncertainty has a negative estimated effect in the US and Mexico, the two countries for which this effect has already been documented, but no other countries in the sample show significant effects. Output uncertainty has a positive effect on output growth for some countries, all of which are more developed, and a negative effect in other countries.

In the next section, I turn to a discussion of the practical size and duration of deficit uncertainty effects in the context of the US quarterly model.

3.5 Discussion

In both the quarterly and monthly models, the US data shows significant negative effects of inflation uncertainty on output, supporting the claims of politicians, news writers, and private sector economists. To understand the quantitative effects of this result, consider a shock to the US quarterly deficit. Let this shock be equal in magnitude to two standard deviations of the average absolute shock estimated as a residual in the full model.

This two standard deviation shock has two effects. The first and larger effect is that the shock increases the deficit, which operates through the VAR to also shock inflation and output. Eventually, the effects of this shock fade out. The second, smaller, effect is that this shock to the deficit causes a persistent increase in deficit uncertainty through the ARCH and GARCH terms in the conditional heteroskedasticity equation. Again, this effect eventually dissipates, but while it is present it has a depressing effect on output growth through the GARCH-M term. Figure 3.1 demonstrates the combined effects of such a change on US inflation, deficit growth, and output growth.

The deficit shock leads to an initial upward shock in output growth of about 0.4% which is gone after approximately 4 quarters. The combined changes in deficit and output cause inflation to fall by a little more than 0.1%. Again, this effect is reversed in about 4 or 5 quarters. After the initial shocks have been reversed, all three series oscillate around their original mean growth rates as the aftereffects wear off. As is evidenced by the direction of the change in the output series, the positive effects of a deficit shock outweigh the negative effects operating through increased uncertainty, making it difficult to determine the magnitude of the uncertainty effects. Figure 3.2 demonstrates the effects of the 2 standard deviation deficit shock only as they operate through the uncertainty channel.

Here, we see the depressing effect uncertainty has on output growth, as estimated growth drops by about 0.1% This estimate is very similar in magnitude and direction to that found by Fernandez-Villaverde et al. (2011). The decrease in output, in turn, causes inflation and deficit growth to drop as well, although by amounts less than one hundredth of one percent. As was the case in Figure 3.1, most of the effects of the shock have dissipated by the time 10 quarters have passed.

While Figures 3.1 and 3.2 describe the reaction of the economy to a one time shock to deficit growth, they do not speak to the effects of a prolonged increase in deficit uncertainty, as many would argue characterizes the US currently. Consider instead a permanent increase in the level of uncertainty. Figure 3.3 shows the results of this change on the economy.

The permanent increase in uncertainty leads to a much larger initial decline in output growth, dropping it by almost half of a percent. While this is somewhat mitigated over time, output growth suffers a permanent decrease of almost 0.2% from this increase in uncertainty. Deficit growth drops initially, but demonstrates no long-term change. Inflation falls steadily by a total of about 0.9% where it levels off, again permanently below its original value. The changes take about 20 quarters to be fully realized before the variables become mostly stable again.

3.6 Conclusion

In this paper, I use a VAR GARCH-M model to test for the effects of deficit uncertainty on output growth. I begin by showing that deficit growth is characterized by persistent conditional heteroskedasticity, as are inflation and output growth in most cases. I then use estimates of the conditional heteroskedasticity as measurements of uncertainty in the GARCH-M model.

Results indicate that, in the US, deficit uncertainty does have a significant depressing effect on output growth, but this result does not apply universally to all countries. Prima facie evidence indicates a possible relationship between level of development and the presence of deficit uncertainty effects on output. Additionally, results indicate that the effects of inflation uncertainty documented in similar works may be limited to a subset of countries or that the inclusion of a deficit series dilutes these measured effects.

The quantitative importance of the results is demonstrated by looking at the economy's response to 1) a one-time shock to the deficit and 2) a permanent increase in deficit uncertainty. While the uncertainty effects of a one-time positive shock are outweighed by the direct effect of the deficit shock itself, the uncertainty does lead to a temporary decrease in output growth of about 0.1%. A permanent increase in uncertainty leads to a permanent drop in both output and inflation.

Table 3.1

Preliminary tests for conditional heteroskedasticity: Quarterly Data

			Ljung-Box Statistics				LR Tests for ARCH Effects						
	Data from:	Series	Q^2_1		Q^2_4		ARCH(1)		ARCH(2)		ARCH(4)		Evidence of Conditonal Heteroskedasticity?
			STAT	P-Value	STAT	P-Value	STAT	P-Value	STAT	P-Value	STAT	P-Value	
Australia	1970 Q2-1998 Q1	Inflation:	**4.272**	**(0.039)**	**28.008**	**(0.000)**	**4.134**	**(0.042)**	**5.696**	**(0.058)**	**24.206**	**(0.000)**	Yes
		Deficit:	2.111	(0.146)	**12.714**	**(0.013)**	2.046	(0.153)	**5.561**	**(0.059)**	**8.008**	**(0.091)**	Yes
		Output:	**6.679**	**(0.010)**	7.565	(0.109)	**6.482**	**(0.011)**	**6.444**	**(0.040)**	6.582	(0.160)	Yes
Barbados	1975 Q4-2007 Q1	Inflation:	0.095	(0.758)	**14.502**	**(0.006)**	0.092	(0.762)	0.087	(0.958)	**13.936**	**(0.008)**	Yes
		Deficit:	**10.755**	**(0.001)**	**11.513**	**(0.021)**	**10.531**	**(0.001)**	**11.850**	**(0.003)**	**12.673**	**(0.013)**	Yes
		Output:	0.135	(0.714)	2.514	(0.642)	0.131	(0.718)	3.428	(0.842)	2.921	(0.571)	No
Jordan	1977 Q4-2000 Q3	Inflation:	2.191	(0.139)	2.6809	(0.613)	2.1054	(0.1468)	2.2223	(0.3292)	2.5571	(0.6344)	No
		Deficit:	2.0059	(0.157)	**9.828**	**(0.043)**	1.9328	(0.1645)	2.2134	(0.3307)	6.9824	(0.1368)	Yes
		Output:	0.0227	(0.88)	**22.6342**	**(0.000)**	0.0218	(0.8825)	**20.6338**	**(0.000)**	**22.8623**	**(0.0001)**	Yes
Korea	1971 Q4-2000 Q3	Inflation:	**4.111**	**(0.043)**	**17.763**	**(0.001)**	**3.990**	**(0.046)**	**4.798**	**(0.091)**	**14.348**	**(0.006)**	Yes
		Deficit:	**3.465**	**(0.063)**	**30.996**	**(0.000)**	**3.386**	**(0.066)**	3.451	(0.178)	**26.371**	**(0.000)**	Yes
		Output:	**4.862**	**(0.027)**	**12.297**	**(0.015)**	**4.712**	**(0.030)**	**6.217**	**(0.045)**	**9.584**	**(0.048)**	Yes
Malaysia	1971 Q1-1991 Q4	Inflation:	**3.2458**	**(0.072)**	3.8118	(0.432)	**3.1565**	**(0.0756)**	3.1001	(0.2122)	3.5145	(0.4757)	Yes
		Deficit:	**7.5902**	**(0.006)**	**28.6181**	**(0.000)**	**23.3065**	**(0.000)**	**33.5174**	**(0.000)**	**38.3805**	**(0.000)**	Yes
		Output:	0.0086	(0.926)	0.0168	(1.000)	0.0223	(0.8814)	0.0338	(0.9833)	0.1156	(0.9984)	No
Mexico	1981 Q4-1997 Q3	Inflation:	1.299	(0.254)	1.5774	(0.813)	1.2268	(0.268)	1.2627	(0.5319)	1.439	(0.8374)	No
		Deficit:	**12.2465**	**(0.000)**	**14.2149**	**(0.007)**	**11.6555**	**(0.0006)**	**12.7164**	**(0.0017)**	**13.5181**	**(0.009)**	Yes
		Output:	0.0753	(0.784)	1.9338	(0.748)	0.0718	(0.7887)	0.6756	(0.7133)	2.0267	(0.7308)	No
US	1969 Q2-2011 Q1	Inflation:	0.0085	(0.927)	3.8367	(0.429)	0.0083	(0.9275)	0.0173	(0.9914)	3.6264	(0.4589)	No
		Deficit:	**30.8746**	**(0.000)**	**38.2128**	**(0.000)**	**30.1915**	**(0.000)**	**33.9573**	**(0.000)**	**39.2338**	**(0.000)**	Yes
		Output:	**7.6683**	**(0.006)**	**18.7168**	**(0.001)**	**7.5**	**(0.0062)**	**11.8232**	**(0.0027)**	**15.0431**	**(0.0046)**	Yes

Table 3.1 (cont.)

Preliminary tests for conditional heteroskedasticity: Monthly Data

			Ljung-Box Statistics				LR Tests for ARCH Effects						Evidence of Conditonal Heteroskedasticity?
	Data from:	Series	Q^2_4		Q^2_{12}		ARCH(4)		ARCH(8)		ARCH(12)		
			STAT	P-Value	STAT	P-Value	STAT	P-Value	STAT	P-Value	STAT	P-Value	
Brazil	1992 M2-2009 M3	Inflation:	**60.863**	**(0.000)**	**65.633**	**(0.000)**	**72.046**	**(0.000)**	**97.555**	**(0.000)**	**104.864**	**(0.000)**	Yes
		Deficit:	**17.758**	**(0.001)**	**38.786**	**(0.000)**	**16.208**	**(0.003)**	**17.196**	**(0.028)**	**43.605**	**(0.000)**	Yes
		Output:	3.750	(0.441)	7.182	(0.845)	3.888	(0.421)	7.145	(0.521)	8.318	(0.760)	No
Korea	1971 M3-2000 M11	Inflation:	3.210	(0.523)	8.654	(0.732)	2.901	(0.575)	8.053	(0.428)	8.363	(0.756)	No
		Deficit:	**170.289**	**(0.000)**	**303.820**	**(0.000)**	**103.848**	**(0.000)**	**103.041**	**(0.000)**	**108.69**	**(0.000)**	Yes
		Output:	**42.343**	**(0.000)**	**48.945**	**(0.000)**	**42.858**	**(0.000)**	**46.217**	**(0.000)**	**48.841**	**(0.000)**	Yes
Mexico	1982 M10-2012 M1	Inflation:	**121.742**	**(0.000)**	**130.297**	**(0.000)**	**140.41**	**(0.000)**	**161.49**	**(0.000)**	**165.624**	**(0.000)**	Yes
		Deficit:	**42.312**	**(0.000)**	**146.091**	**(0.000)**	**36.727**	**(0.000)**	**43.660**	**(0.000)**	**81.081**	**(0.000)**	Yes
		Output:	**29.715**	**(0.000)**	**36.440**	**(0.000)**	**30.889**	**(0.000)**	**34.005**	**(0.000)**	**33.935**	**(0.001)**	Yes
US	1969 M2-2011 M4	Inflation:	**101.518**	**(0.000)**	**116.777**	**(0.000)**	**80.680**	**(0.000)**	**82.766**	**(0.000)**	**88.034**	**(0.000)**	Yes
		Deficit:	**68.849**	**(0.000)**	**137.411**	**(0.000)**	**62.669**	**(0.000)**	**65.310**	**(0.000)**	**81.891**	**(0.000)**	Yes
		Output:	**40.204**	**(0.000)**	**46.867**	**(0.000)**	**37.677**	**(0.000)**	**38.588**	**(0.000)**	**45.095**	**(0.000)**	Yes

Table 1 shows the preliminary tests for conditional variance, first for the quarterly datasets and then for the monthly. Ljung-Box statistics are shown for 1 and 4 quarter lags, or for 4 and 12 month lags. Likelihood Ratio tests for ARCH effects are calculated for 1, 2, and 4, quarters or for 4, 8, and 12 months. For one series (Brazilian output), preliminary tests didn't indicate conditional variance, but evidence was found in the fuller model, so the final model for Brazil includes an ARCH process, even though it isn't suggested by the preliminary evidence. Bold values indicate statistical significance at the 10% level.

Table 3.2

Conditional Heteroskedasticity and GARCH-M results from the full model: Quarterly Data

	Series	Conditional Variance Form	Constant	ARCH(1) term	ARCH(2) term	GARCH term	Uncertainty parameters		
							σ_{inf}	σ_{def}	σ_{out}
Australia	Inflation:	GARCH(1,1)	8.41 e -6 **	1.577 ***		0.024	0.236	-0.006 **	0.843
			(3.86 e -6)	(0.406)		(0.039)	(0.268)	(0.003)	(0.648)
	Deficit:	GARCH(1,1)	0.002	0.258 ***		0.806 ***			
			(0.028)	(0.092)		(0.067)			
	Output:	ARCH(1)	1.72 e -4 ***	0.399 **					
			(3.80 e -5)	(0.180)					
Barbados	Inflation:	GARCH(1,1)	1.7 e -5	0.716 ***		0.385 ***	0.172	1 e -6	
			(1.2 e -5)	(0.192)		(0.112)	(0.408)	(2 e -5)	
	Deficit:	ARCH(2)	49252 **	0.429 ***	0.315				
			(24023)	(0.177)	(0.295)				
	Output:	Constant Var.	0.001 ***						
			(0.0002)						
Jordan	Inflation:	Constant Var.	3.9 e -4 ***					0.000	-0.365 ***
			(5.5 e -5)					(4.8 e -5)	(0.106)
	Deficit:	GARCH(1,1)	16758	0.157		0.717 ***			
			(12180)	(0.102)		(0.163)			
	Output:	ARCH(1)	7.8 e -4 ***	1.517 ***					
			(2.7 e -4)	(0.395)					
Korea	Inflation:	GARCH(1,1)	6.8 e -6 **	0.767 ***		0.468 ***	0.325	1.2 e -6	-0.668 ***
			(3.4 e -6)	(0.262)		(0.093)	(0.207)	(1.9 e -6)	(0.137)
	Deficit:	ARCH(1)	0.038	5.728 ***					
			(0.075)	(0.709)					
	Output:	GARCH(1,1)	1.3 e -4 ***	1.069 ***		0.001			
			(4.2 e -5)	(0.265)		(0.054)			
Malaysia	Inflation:	ARCH(1)	3.3 e -5 ***	0.642 *			0.767	3.4 e -5	
			(1.0 e -5)	(0.353)			(1.925)	(5.0 e -5)	
	Deficit:	ARCH(1)	5554 **	1.424 ***					
			(2249)	(0.452)					
	Output:	Constant Var.	0.002 ***						
			(0.0003)						
Mexico	Inflation:	Constant Var.	0.001 ***					1.3 e -5 **	
			(0.0002)					(6 e -6)	
	Deficit:	ARCH(1)	1955	2.704 ***					
			(1668)	(0.653)					
	Output:	Constant Var.	4.4 e -4 ***						
			(7.9 e -5)						
US	Inflation:	Constant Var.	1.5 e -5 ***					-2.2 e -5 ***	1.376 ***
			(1 e -6)					(6 e -6)	(0.358)
	Deficit:	GARCH(1,1)	3.488	0.477 ***		0.704 ***			
			(40.990)	(0.096)		(0.042)			
	Output:	GARCH(1,1)	5 e -6	0.214 ***		0.760 ***			
			(3 e -6)	(0.063)		(0.049)			

Table 3.2 (cont.)

Conditional Heteroskedasticity and GARCH-M results from the full model: Monthly Data

	Series	Conditional Variance Form	Constant		ARCH(1) term		ARCH(2) term		GARCH term		Uncertainty parameters σ_{inf}		σ_{def}		σ_{out}	
Brazil	Inflation:	GARCH(1,1)	20.479	***	1.149	***			0.252	***	0.074		0.006		-0.431	**
			(6.257)		(0.230)				(0.083)		(0.061)		(0.004)		(0.208)	
	Deficit:	GARCH(1,1)	228138	***	0.708	***			0.038							
			(48626)		(0.185)				(0.110)							
	Output:	ARCH(1)	318.58	***	0.644	***										
			(47.16)		(0.182)											
Korea	Inflation:	Constant Var.	161.353	***									-0.335		2.141	***
			(2.640)										(1.397)		(0.069)	
	Deficit:	GARCH(1,1)			1.740	***			0.254	***						
					(0.107)				(0.025)							
	Output:	GARCH(1,1)	370.586	***	0.081	*			0.287	***						
			(30.193)		(0.043)				(0.035)							
Mexico	Inflation:	GARCH(1,1)	4.714	**	0.735	***			0.434	***	-0.518	***	-0.001	*	1.489	***
			(1.843)		(0.056)				(0.023)		(0.145)		(0.0006)		(0.098)	
	Deficit:	ARCH(2)	0.0002		1.730	***	1.415	***								
			(0.0004)		(0.090)		(0.190)									
	Output:	ARCH(1)	427.965	***	0.245	***										
			(36.547)		(0.057)											
US	Inflation:	GARCH(1,1)	2.218	***	0.688	***			0.453	***	-0.019	***	-0.0009	**	0.303	***
			(0.286)		(0.045)				(0.022)		(0.002)		(0.0004)		(0.043)	
	Deficit:	GARCH(1,1)	0.0003		2.756	***			0.168	***						
			(0.0008)		(0.085)				(0.007)							
	Output:	GARCH(1,1)	20.489	***	0.595	***			0.176	***						
			(2.800)		(0.051)				(0.037)							

Table 2 provides selected results from the full model. T-statistics are in parentheses below point estimates. The constant term for the monthly deficit series for Korea was ommitted because the maximization routine assigned it a small, negative value which violates the model's constraints.

* p-value <0.1   ** p-value<0.05   *** p-value<0.001

Table 3.3						
Ex Post tests for conditional heteroskedasticity: Quarterly Data						
	Series	Ljung-Box Statistics Q^2_1		Q^2_4		Evidence of Conditonal Heteroskedasticity?
		STAT	P-Value	STAT	P-Value	
Australia	Inflation:	0.1850	(0.667)	4.4848	(0.344)	No
	Deficit:	0.0016	(0.968)	1.7627	(0.779)	No
	Output:	0.1020	(0.749)	1.0867	(0.896)	No
Barbados	Inflation:	0.0601	(0.806)	1.1599	(0.885)	No
	Deficit:	1.0896	(0.297)	2.8475	(0.584)	No
	Output:	0.1335	(0.715)	2.6387	(0.620)	No
Jordan	Inflation:	2.1358	(0.144)	2.5278	(0.640)	No
	Deficit:	0.0744	(0.785)	0.6048	(0.963)	No
	Output:	0.2709	(0.603)	1.1854	(0.880)	No
Korea	Inflation:	0.1669	(0.683)	0.7718	(0.942)	No
	Deficit:	0.1149	(0.735)	0.6809	(0.954)	No
	Output:	0.1152	(0.734)	0.8904	(0.926)	No
Malaysia	Inflation:	0.0341	(0.853)	0.5389	(0.970)	No
	Deficit:	0.9982	(0.318)	1.8228	(0.768)	No
	Output:	0.1933	(0.660)	0.2911	(0.990)	No
Mexico	Inflation:	1.6734	(0.196)	2.0181	(0.732)	No
	Deficit:	1.2427	(0.265)	5.1278	(0.274)	No
	Output:	0.0158	(0.900)	0.8601	(0.930)	No
US	Inflation:	0.008	(0.929)	3.4461	(0.486)	No
	Deficit:	0.6937	(0.405)	2.2402	(0.692)	No
	Output:	0.2676	(0.605)	0.5719	(0.966)	No

Table 3.3 (cont.)						
Ex Post tests for conditional heteroskedasticity: Monthly Data						
	Series	Ljung-Box Statistics Q^2_4		Q^2_{12}		Evidence of Conditonal Heteroskedasticity?
		STAT	P-Value	STAT	P-Value	
Brazil	Inflation:	1.658	(0.798)	15.196	(0.174)	No
	Deficit:	8.774	(0.118)	16.716	(0.161)	No
	Output:	4.029	(0.402)	13.853	(0.310)	No
Korea	Inflation:	3.186	(0.527)	8.750	(0.724)	No
	Deficit:	2.731	(0.604)	4.586	(0.970)	No
	Output:	0.608	(0.962)	7.895	(0.793)	No
Mexico	Inflation:	3.905	(0.419)	6.697	(0.877)	No
	Deficit:	0.397	(0.983)	1.749	(1.000)	No
	Output:	0.797	(0.939)	9.809	(0.633)	No
US	Inflation:	6.075	(0.194)	11.664	(0.473)	No
	Deficit:	3.545	(0.471)	6.660	(0.879)	No
	Output:	1.445	(0.836)	6.183	(0.907)	No

Table 3 presents the ex post results for tests for lingering conditonal heteroskedasticity effects. No series show any evidence of conditional variance beyond that already captured.

Figure 3.1

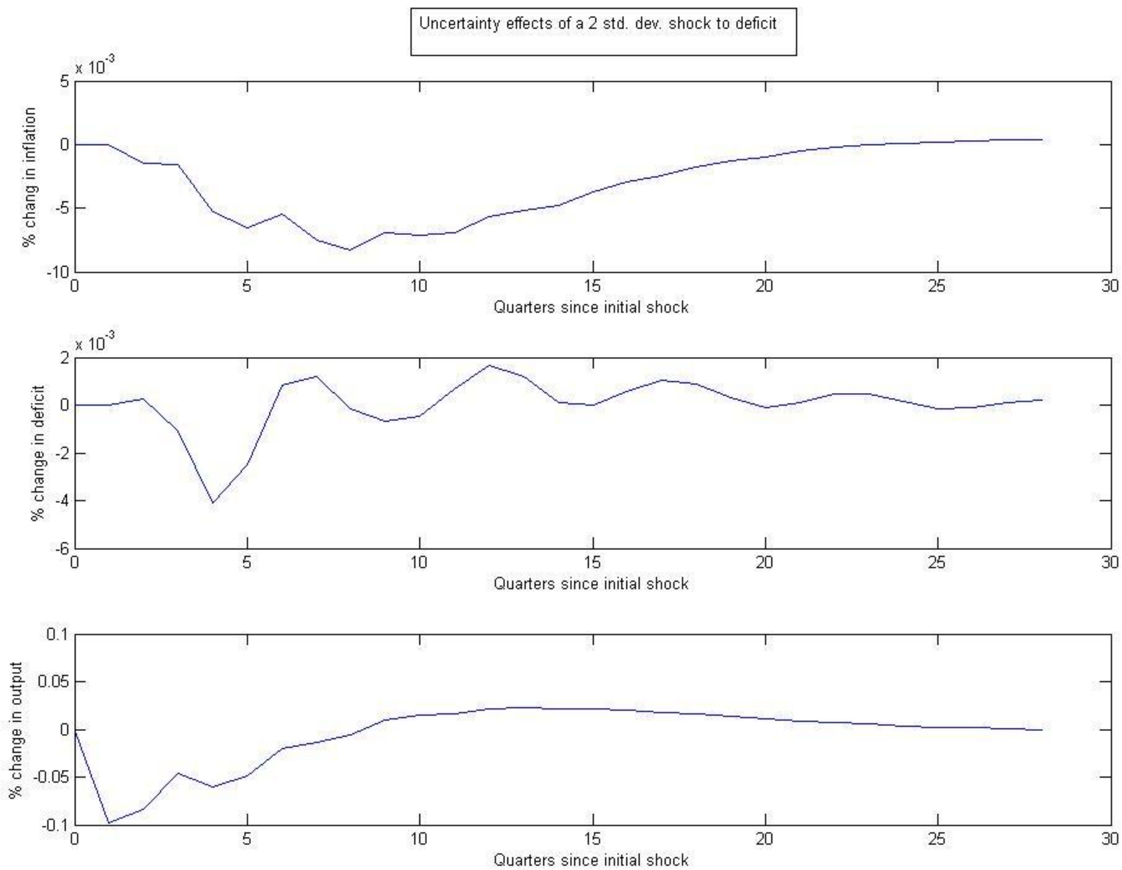

Figure 1 shows the net effect of a 2 standard deviation shock to the deficit. Percentage changes are calculated relative to the average value of a series.

Figure 3.2

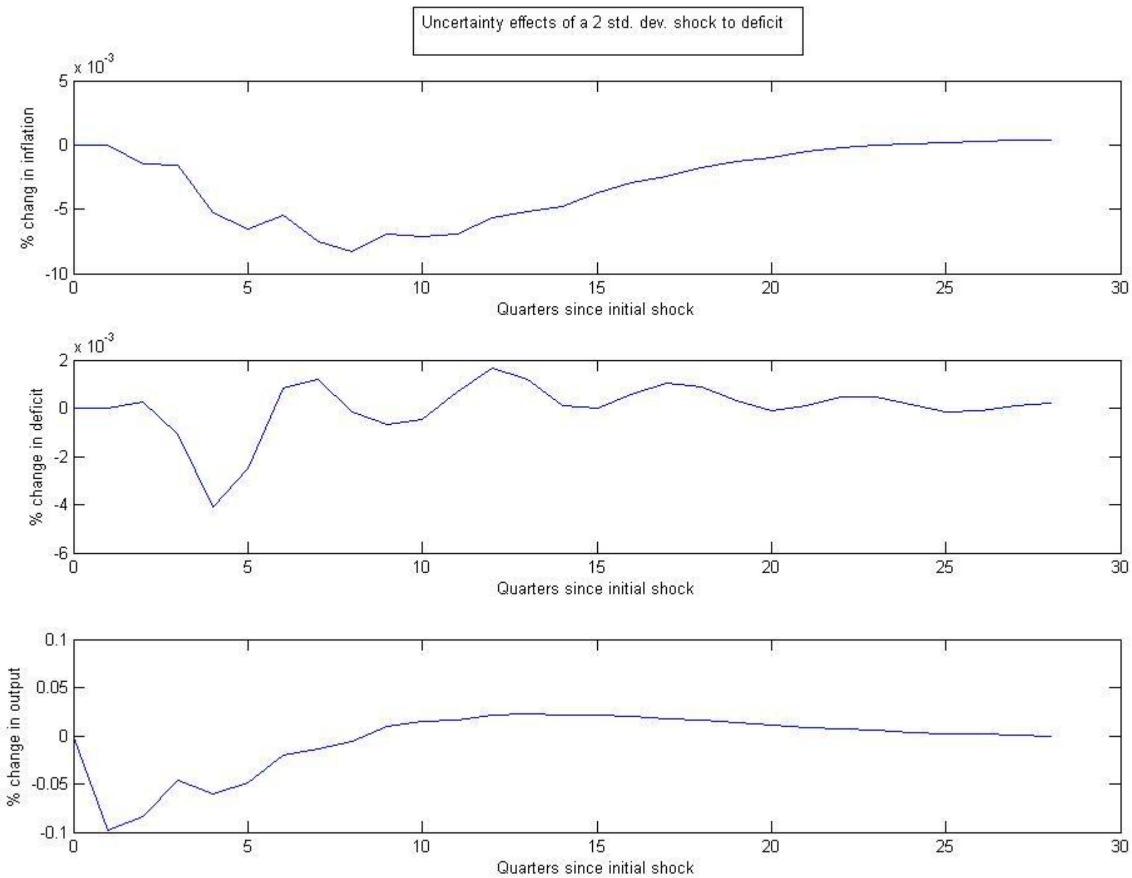

Figure 2 shows only the uncertainty effect of a 2 standard deviation shock to the deficit. Percentage changes are calculated relative to the average value of a series.

Figure 3.3

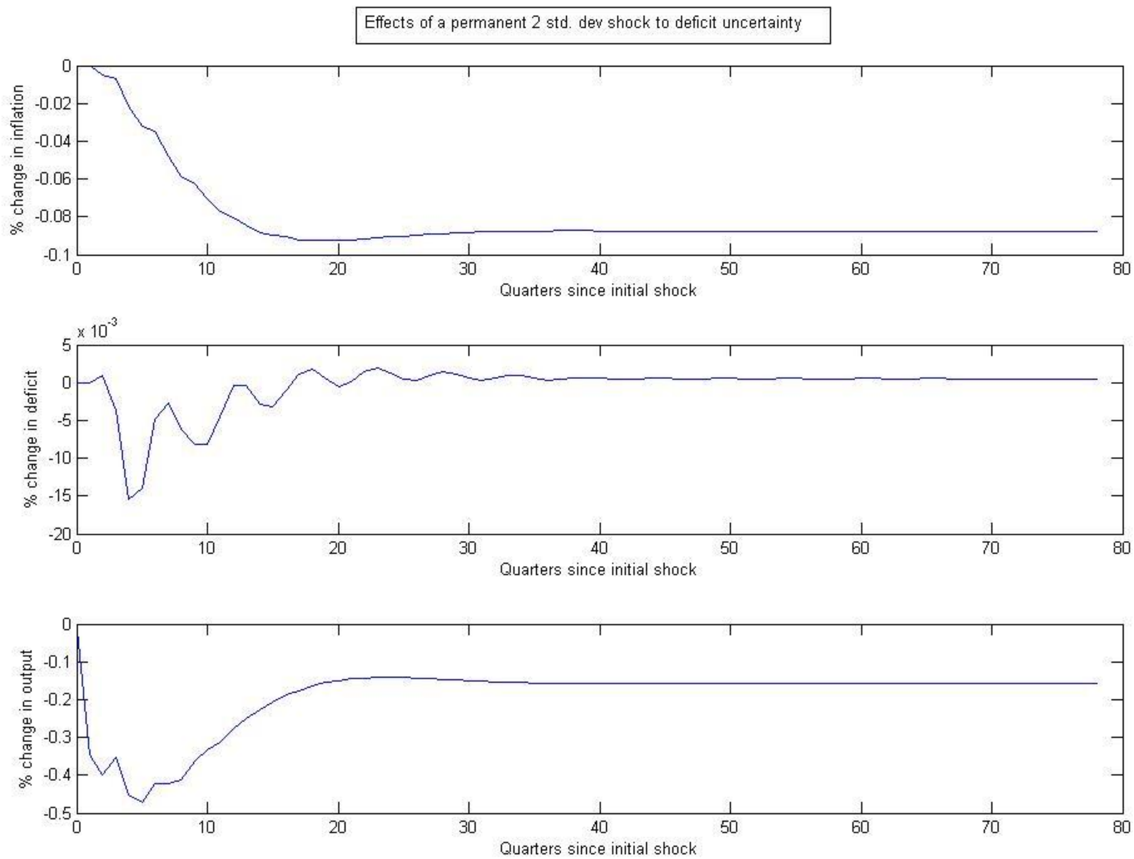

Figure 3 shows the effect of a permanent 2 standard deviation shock to deficit uncertainty. Percentage changes are calculated relative to the average value of a series.

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Appendix A: Data Appendix to Chapter 1

Table A1: Chapter 1 Data sources

Variable	Description	Source	Notes
$Y_{i,t}$	Real GDP in country i at time t	Penn World Tables v. 6.3	
$K_{i,t}$	Stock of Physical Capital in country i at time t	Penn World Tables v. 6.3	Constructed from investment series using perpetual inventory method
$L_{i,t}$	Labor force in country i at time t	Penn World Tables v. 6.3	Constructed using GDP/Capita and GDP/Worker
$H_{i,t}$	Average educational attainment age 15+ in country i at time t	Barro and Lee (2010)	
$INF_{i,t}$	Electrical generating capacity per capita in country i at time t	David Canning	
$HEALTH_{i,t}$	Average Life Expectancy in county i at time t	World Development Indicators	
$NUTR_{i,t}$	Average daily caloric intake in country i at time t	UN Food and Agricutural Organization	
$RDA_{i,t}$	Sqaure root of the ratio: NUTR/2500		Scaled by the recommended daily allowance of calories for an adult male
$OECD_{i}$	Dummy variable indicating if country was a member of the OECD in 2010	OECD	

Table A2: Countries Included in Chapter 1

Algeria	Gambia	Nicaragua
Argentina	Ghana	Niger
Australia	Greece	Norway
Austria	Guatemala	Panama
Barbados	Haiti	Paraguay
Belgium	Honduras	Peru
Benin	Hungary	Philippines
Bolivia	Iceland	Portugal
Botswana	India	Rwanda
Brazil	Indonesia	Senegal
Burundi	Iran	Sierra Leone
Cameroon	Ireland	South Africa
Canada	Israel	Spain
Central African Republic	Italy	Sri Lanka
Chile	Jamaica	Sweden
Colombia	Japan	Switzerland
Congo	Jordan	Syria
Costa Rica	Kenya	Thailand
Cote d'Ivoire	Luxembourg	Togo
Cyprus	Malawi	Trinidad and Tobago
Congo (DRC)	Malaysia	Tunisia
Denmark	Mali	Turkey
Dominican Rep.	Mauritania	Uganda
Ecuador	Mauritius	United Kingdom
Egypt	Mexico	U. Rep. of Tanzania
El Salvador	Morocco	USA
Fiji	Mozambique	Venezuela
Finland	Nepal	Zambia
France	Netherlands	Zimbabwe
Gabon	New Zealand	

Appendix B: Procedure Appendix to Chapter 1

The primary models to be estimated are represented by equations (1.9) and (1.10) in the text. In equation (1.9), capital stocks, infrastructure, labor supply, health, and human capital stocks are all treated as potentially endogenous. In equation (1.10), all RHS variables are considered endogenous. To correct for potential endogeneity in the levels regression in (1.9), instruments are formed using population age breakdown variables representing the fraction of a country's population in each five year category from 0-5 up to 75-80 and a single category for population age 80+. I denote these variables a05-a80 and a80plus. To allow for differential effects of population age on my endogenous variables in OECD and non-OECD countries, the population breakdown variables are interacted with O, a dummy variable for OECD countries, and N, a dummy variable for non-OECD countries. This generates 34 potential instruments, half of which are non-zero for any given country. To instrument for the endogeneity in the growth regression (10), I use the percentage change of the population fraction in each category, %Δa05-%Δa80plus. Once again, this vector is interacted with the OECD and non-OECD dummy variables.

According to the theories which establish these instruments as valid (as discussed in the main text), a relationship exists between the population age breakdowns and the total stocks of capital, labor, and human capital, not with the natural logs of these stocks. Therefore, I instrument first, and then take the natural logs of the predicted values from the first stage.

Because different countries have such vastly different stocks of direct inputs, and because I have data on so many potential instruments, one consequence of the instrumentation process is that predicted values in the first stage can actually wind up being negative for some country-years. To eliminate this issue, the direct inputs in the first stage are scaled down to be a fraction of their respective values in 1970, then regressed on the vector of instruments, and lastly scaled back up.