Estimating Conditional Functional Multipliers

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Abstract

Spending–based fiscal adjustment requires decisions on where– and how much – to cut public spending to minimise adverse effects on economic growth. This requires precise estimates of the response of output to changes in the functional components of public spending. I call this the *functional multiplier*. I I disaggregate government spending in 36 low-income countries over the period 1984 -2013 into its functional components. Using a GMM-IV model with fuel subsidies as the instrument for government spending I exploit differences in the length of exposure to statehood as a proxy for current absorptive capacity to estimate functional multipliers conditional on absorptive capacity.The estimated functional multipliers vary from -1.11 for economic services to 1.82 for social protection. I find that a one standard deviation change in absorptive capacity yields a 18% larger multiplier compared to the average level of absorptive capacity. A similar exercise for contestability shows that a one standard deviation change in contestability yields a 14% larger multiplier compared to the average level of absorptive capacity. I subject the GMM-IV estimates to a rigorous test to determine whether the estimated relationships are causal and not simply spurious correlation. Post-double LASSO estimates show that that the conditional functional multipliers are precisely estimated and of the same order of magnitude (though slightly larger) than the GMM-IV estimates. To obtain multipliers for individual countries (and not averages) I use a Bayesian Iterative shrinkage estimators. The shrinkage estimates show that countries with higher than average absorptive capacity have multipliers that are 15% larger than those below the average.

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1. INTRODUCTION

The Afghan economy finds itself in the eye of a perfect storm. The rapid decline in international military spending as a result of the drawdown of international troops constituted a major negative demand shock. This has resulted in a sharp economic slowdown, with growth of the country's overall gross domestic product tumbling from 14.4 percent in 2012 to 1.3 percent in 2015. Domestic revenue collection collapsed because of lower growth, declining imports, and lower tax compliance. Operating expenditures increased, as off-budget security-related spending was moved on- budget. The weakening economy reflects loss of business and consumer confidence, lack of private investment and low and declining public investment. Capital flight and human flight, already significant, mushroomed over the past two years as Afghans risked their lives crossing the Mediterranean. The dire economic situation has been exacerbated by intensifying violent conflict as the Taliban control over 20 of 34 provinces and the national unity government appears paralyzed to take decisive action to mend the economy and beat back the insurgents.

The Afghan situation is worse than most but many low-income countries have experienced similar difficulties. In such dire situations few would argue against putting in place some variant of a spending-based fiscal consolidation. As long as it imposes as little cost as possible to economic growth while prioritizing growing spending needs and making sure that scarce resources are spent efficiently.[1] Fiscal adjustment, is of course, worthwhile if it has growth promoting effects or, at the very least, if it does not lead to a net decline in aggregate demand. Does it? Surprisingly, there is no clear answer to this question because there is very little empirical research about the response of output to changes in government spending in low-income countries (LICs). The few papers that estimate government spending effects in LICs are Kraay (2012, 2014) and Iletzki et al (2011). Kraay use datasets of official creditors' lending to developing countries, including Low Income Countries. In both papers, Kraay estimates that the short-run output multiplier is about 0.4. Ilzetzki et al (2011) find that their estimate of the multiplier is not significantly different from zero for countries with a flexible exchange rate and they find the multiplier is smaller for more open economies.

This paper makes progress in closing this gap. I disaggregate government spending in 30 low-income countries into its functional components according to the Classification of Functions of Government (COFOG). I then estimate of the response of output to functional components of public spending conditional on absorptive capacity– what I refer to as conditional functional multipliers. Absorptive capacity is a key structural characteristic of low-income

[1] After the 2008 Great Recession out of 86 low and middle income countries, about 40 per cent engaged in reductions in public expenditure in 2010-2011 relative to 2008-2009. The average projected spending cuts were around 2.6 per cent of GDP.

countries which has not been studied in relation to the multiplier literature.[2]To measure absorptive capacity across countries I use the State Antiquity Index of Bockette and Putterman (2002). The State Antiquity index is based on the number of years ("state history") since the territory within the borders of a modern country acquired a form of government more centralized than just a tribe, i.e., a chiefdom or state or empire. State history is a plausible proxy for absorptive capacity, because the emergence of centralized government was associated with the development of competent bureaucrats, further growth of technology, population, social complexity, and market economies. Bockette (2002) demonstrates that state antiquity is a good instrument for institutional quality in regressions that aim to explain long-run development.

To estimate conditional functional multipliers requires a model that can account for both unit and time-varying correlated unobserved heterogeneity in the multiplier estimates. This is because countries are heterogeneous in their fiscal reaction functions: following a fiscal shock, different countries will conduct fiscal consolidation using different instruments, at different levels and over different horizons. Countries are also heterogeneous with respect absorptive capacity and other structural characteristic of low-income countries such as home bias.

One way to incorporate heterogeneous marginal effects into a regression framework is the correlated random coefficients model (CRC) developed by Chamberlain (1992) where the panel dimension of the data helps identify the average partial effect of the functional components of government spending on output. and address potential endogeneity concerns from time-varying omitted variables.

I estimate a CRC model with the standard GMM-IV where be included in the model are intuitively selected. I use a selectivity bias correction method proposed by Garen (1984), as well as a fixed-effect instrumental estimator shown by Murtazashvili and Wooldridge (2008) to be consistent under correlated heterogeneity to identify the conditional functional multiplier. The instrumental variable I use exploits cross-country differences in fuel subsidies schemes that induce variation in government expenditures when exposed to fluctuations in oil prices. The estimated average conditional instrument multipliers range from -1.11 for economic affairs to 1.82 for social protection. These estimates are markedly different from the standard multiplier of Kraay (2012,2014) which is about 0.4. Furthermore, I find that a one standard deviation change in absorptive capacity yields a 18% larger multiplier compared to the average level of absorptive capacity. Furthermore, I find that a one standard deviation change in contestability yields a 18% larger multiplier compared to the average level of absorptive capacity. The results are robust to inclusion of an extensive list of controls, alternative definitions of absorptive capacity, and exclusion of influential observations.

Despite having passed the robustness test there is still some concern that the GMM-IV estimates may not be causal and simply a correlation. One weakness in the standard GMM-IV

[2]By absorptive capacity I am referring to the transparency and efficiency of budget systems, the expertise and management capacity of bureaucrats, mechanisms to define policy priorities and accountability systems to hold governments responsible.

approach is that the control variables are selected intuitively. With the recent explosion in computing power, contemporary researchers are faced with high-dimensional datasets. From weather variables, satellite images of night lights, to latitude and longtitude, other spatial geographic variables such as distances, political variable, legal and the list goes on. Add to this list squared and cubic terms products of variables and the list can grow into the thousands.

How can one be sure that the control variables they have included in the model are the appropriate ones? Model selection—choosing the correct covariates to include in an empirical model–is a critical step in any empirical research. Including too many controls increases the variance of the model, and taking fewer controls than needed results in inconsistent estimates. When valid controls are excluded, the estimated coefficient of interest may either be artificially strong (when the control is a confound), or may be artificially weak (a suppression effect).

Recently developed methods based on LASSO regression (e.g. Tibshirani, 1996) provide a useful solution to the problems of model selection in high-dimensional data. In this paper I use the double-lasso approach (Belloni et al., 2014) to select variables for inclusion in the regression model in a principled manner that avoids inflated Type I errors. The goal is to identify covariates for inclusion in two steps, finding those that predict the dependent variable and those that predict the independent variable. The second step is important, because exclusion of a covariate that is a modest predictor of the dependent variable but a strong predictor of the independent variable can create a substantial omitted variable bias. The variables selected in either step are then included in the regression of interest. The post double-LASSO estimator of Belloni *et al.* 2012 provides a structured way to determine whether the estimates from the intuitively selected control variables are sound. Application of the post double LASSO estimator to the GMM-IV data does not invalidate our findings. The estimated conditional functional multipliers are precisely estimated and of the same order of magnitude (though slightly smaller) thanthe GMM-IV estimates.

To obtain multipliers for individual countries I use shrinkage-type estimators.[3] The term shrinkage refers to a statistical phenomenon that the posterior estimate of the prior mean is shifted from the sample mean towards the prior mean. The Bayesian approach to the shrinkage estimation is to use the prior distribution and the likelihood (based on the data) to determine the posterior distribution. It has been regarded as empirical Bayes shrinkage (EBS), when there is no information for the prior and the observed data are employed to postulate the prior distribution, assuming the sample means were drawn from the same population. The multipliers estimated with the shrinkage estimators are slightly larger than those estimated by the average multipliers estimated by post-double LASSO estimator. There is a clear ranking that emerges from the shrinkage estimates. Countries with higher absorptive capacity have

[3]These estimators are related to the James-Stein (J-S) estimator, James and Stein, (1962) and can all be understood from an empirical Bayes point of view as pointed out by Efron and Morris (1972). A modern formulation is by penalized likelihood Hastie and Tibsharani (1986) and the LASSO of Tibsharani (1996) and the Garotte of Breiman (1995).

larger multipliers.

This paper makes four key contributions to the literature. First, the methodological innovations in the paper — disaggregating spending into its functional components, allowing for multipliers to be conditioned on absorptive capacity, dealing with unobserved heterogeneity in a correlated random coefficient model estimated with LASSO-based methods that select controls – have led to the first, precise and robust estimates of conditional multipliers for low-income countries.

Second, this paper underscores the importance of absorptive capacity in amplifying or attenuating the impact of government spending on output. The lack of absorptive capacity is a key characteristic of low-income countries. Yet, to the best of my knowledge, this is the first paper to conduct a systematic empirical analysis that incorporates robust and credible measures of absorptive capacity. The results show that the size of the multiplier is increasing in absorptive capacity.

Third, by taking a granular look at the response of output to various components of spending I am able to untangle the impact of each category of spending on output. Such a granular look is important. For example, I estimate that the average multiplier from social protection (transfer) in this sample of thirty low-income countries is 1.11. The magnitude of my transfer multiplier compares favorably with recent estimates of the transfer multiplier from the Great Depression. Fishback and Kachanovskaya (2013) examine the impact of federal stimulus programs during the Great Depression on a state-by-state basis. They estimate that for personal income, which includes transfer payments, the multiplier ranges from 0.91 for a combination of government grants and loans to 1.39 when only grants are considered.

Finally, this paper illustrates how cutting edge methods from statistical theory and machine learning can be used to generate robust estimates of conditional functional multipliers. These advance in statistical methods are another milestone in our journey away from correlation to causality.

The rest of the paper is organized as follows. Section 2 explains how I compiled the cross-country data on government spending disaggregated by functional components; how absorptive capacity is calculated. Section 3 motivates the use of the correlated random coefficient panel date model. In section 4 I estimate conditional functional multipliers by GMM-IV and discuss the results and a battery of robustness tests. In Section 4 I subject the data I used in the GMM-IV to the post-Double LASSO estimator. In section 5 I estimate individual country multiples with shrinkage type estimators. Section 6 concludes. A Supplemental Appendix includes all thw data and replication code.

2. Data and Measurement

In this section I describe the main variables used in the empirical analysis. Summary statistics for all variables as well as detailed data sources, are reported in the Supplementary Appendix.

2.1. Disaggregated Government Spending

I use annual time-series data on public expenditures at disaggregated levels, for 36 developing countries over the period 1976–2013. The primary source of this data is the IMF Government Financial Statistics (GFS) dataset. I use the GFS data on government expenditures, which includes all non-repayable payments by any level of government for either current or capital purposes. GFS classifies expenditure by two methods: either by economic characteristics or by the function or purpose served. I used the latter. The classification of the functions of government (COFOG) breaks total expenditure into categories such as healthcare, education, and defense. The raw data is gross expenditure in local currency so I divide by the contemporaneous GDP in local currency to achieve expenditure as a share of GDP, which is a unit-less measure. So a sample GFS series would be expenditure by the central government on education as a share of GDP and observations would be by country-year. For countries with missing or incomplete data I obtained data from the management informaion systems and Central Government Consolidated accounts of the respective these countries.

2.2. Absorptive Capacity

The concept of absorptive capacity has a long and distinguished history in development economics dating back to the 1950s. In the early literature it was used in reference to the ability of the government to effectively utilize foreign aid. Here it is conceptualized as the ability of the government identify, attract and efficiently use financial resources (domestic and external). Key to this concept of absorptive capacity is the prevalence of modern management practices and skilled manpower in the public sector.

One early commentator notes that "In practice, however, economic growth depends heavily on the availability of skilled workers, managers, technical personnel and civil servants. The lack of these skills can severely limit the amount of productive investment which can be planned, organized and executed and sets what is commonly called the absorptive capacity of an economy. Chenery (1965) Absorptive capacity is thus conceptualized as the governments latent ability to marshal, develop, direct, and control its human, physical and information capital to support the discharge of its policy directions. Its important to note that States have many capacities: administrative, coercive and extractive. It is useful to think of absorptive capacity as a subset of administrative capacity. They capacities of a state are not mutually exclusive. For example, coercive capacity requires administrative capacity to raise revenue to purchase weapons.

High absorptive capacity governments have a combination of strong policy formulation abilities and skilled technocrats, which enable them to be adaptable, effective and efficient in translating financial resources into tangible public investments. Low absorptive capacity governments fail to translate financial resources into tangible public investments.

To operationalize the concept of absorptive capacity it must be measured. The State Antiquity Index (Version 3) developed by Bockstette and Putterman (2007) from 3500 BCE forward for all countries in the world is the best available measure of absorptive capacity. Bockstette and Putterman (2007) show that state antiquity is a robust instrument for modern day institutional quality in regressions that aim to explain long-run development. Using the same data, Borcan, Olsson and Putterman (2015) show that the presence of a state is one of the most reliable historical predictors of social and economic development.

The State Antiquity Index is based on the plausible intuition that longer a nation has had of a history of statehood the higher the quality public administration due to "learning by doing effects. Perhaps nothing is more central to the concept of state capacity than raising revenue. North defines the boundaries of the state in terms of its ability to tax constituents (1981: 21), while Levi (1988) and Tilly (1990) make a direct connection between a states revenue and the possibility to extend its rule. Raising revenue is not only a critical function of the state, but it also encompasses a particular set of capacities that are foundational to state power. In particular, states must have the wherewithal to reach their populations, collect and manage information, possess trustworthy agents to manage the revenue, and ensure popular compliance with tax policy.

The logic relating the length of statehood and modern day absorptive capacity is straightforward: accomplishing policy goals of almost any kind requires financial resources. States that have had a longer history of tapping and using resources efficiently and effectively will in general be more successful at achieving their developmental goals today.

To further clarify the relationship between the length of statehood (state antiquity) and absorptive capacity consider the case of Afghanistan. Beginning around 1000 years ago, the Turko-Mongolian and Islamic empires competed for control of the land that is present-day Afghanistan (Barfield, 2010: 9296). Despite domination by a host of foreign empires, Afghanistans customary and tribal forms of authority remained strong, in large measure because of the Turko-Mongol penchant for indirect rule. During the period 1747 to 1880, the territory known today as Afghanistan bore little resemblance to a modern state.

Afghanistan came into existence when a Loya Jirga (Grand Council) of local tribal and customary power brokers selected Ahmad Shah as the leader of the Afghan tribes in 1747. From 1747 until 1880, the extent to which Afghan sovereigns enjoyed a monopoly on coercion was nonetheless tenuous. The country was a loose collection of quasi–autonomous regions headed by governors with few ties to the monarchy. The central government had almost no bureaucratic capacity, and the army only organized in an ad hoc fashion in response to threats. Despite profound state weakness, a system of simple land use rights emerged during this period.

Yet it was Amir Abdur Rahman, who was finally able to raise a standing army and improve bureaucratic capacity from 1880 to 1901. Although Amir Dost Mohammed, who founded the Mohammadzai dynasty in 1826, and his son, Sher Ali, made some headway in unifying the Afghan state, it was Abdur Rahman who finally brought the various tribes of Afghanistan under direct political control. According to the definition of a strong state—one that can penetrate society, regulate social relations, extract resources, and use those resources effectively—Abdur Rahman constructed a state stronger than any previous Afghan monarch.

Abdur Rahman, who earned a reputation as the “Iron Amir" for the violence with which he dealt with his adversaries, expanded state ownership, implemented violent repopulation campaigns, and sharply increased taxation throughout his reign. The data for state antiquity index spans 6 millennia so Afghanistan has a relatively short history of statehood and thus today is likely to have low absorptive capacity.

The State Antiquity Index is constructed by scoring each of the 39 half-centuries from year 1 to 1950 by answering three questions (scores in parentheses): (a) Is there a government above the tribal/chiefdom level? (1 if yes, 0.75 if chiefdom, 0 if tribe); (b) Is the government locally based? (1 if yes, 0.75 if there is a local government with substantial foreign oversight, 0.5 if foreign based); (c) How much of the present-day countrys territory was ruled by the historical government? (1 if more than 50%; 0.75 if between 25% and 50%, 0.5 if between 10% and 25%, 0.3 if less than 10%). Scores from the three questions are multiplied for each half-century, and the index of state history is computed by summing the discounted value of the scores for the 39 half-centuries.

2.3. *Contestable Markets*

A second characteristic of low—income countries that is likely to mediate the effect of government spending on real GDP growth — is contestability.

To understand the importance of contestable markets for the fiscal multiplier consider for a moment what happens when the government “spends”. Government “spending” means the government goes to the market and buys goods and services from businesses. The manner in which businesses supply the government— from the quality of the goods and services supplied, the prices and quantities of the goods and services supplied, the speed with which the goods and services are supplied, depends on the prevailing market structure. Is the market structure perfectly competitive, oligopolistic, monopolistic competitive or monopolistic? Traditional economic theory says that a perfectly competitive market structure in which there are many firms competing to supply high quality goods and services is the most efficient way to satisfy market demand at the lowest price, while creating jobs and boosting economic prosperity.

Moving from theory to reality it is evident that in low–income countries the conditions for perfect competition are far from being met and the possible benefits of competition do not necessarily always translate into lower prices, better quality goods, job creation and faster economic growth. At the same time, efforts to deregulate markets that are intended to benefit consumers do not always work. For example, the consumer welfare and developmental benefits resulting from trade and investment liberalization and privatization, in the absence of the appropriate competition rules and supporting institutional infrastructure, have been questioned in the light of the experiences of many low–income countries.

Recent events in Afghanistan underscore this predicament. In the Asia Foundation's 2015 Survey of the Afghan People, citizens who believed the country was going in the right direction declined to 37 per cent from 55 percent in 2014. The Survey shows that the Afghan public increasingly links the worsening economy with the government's policies on free markets and/or inability to perform. While the national unity government has prioritized the economy in its policy reform agenda, popular expectations created by the rhetoric of a free market economy have yet to be matched by a track record in creating jobs and delivering high quality goods at low prices.

According to the most recent Afghanistan Living Conditions Survey, the unemployment rate rose from 9.3 per cent in 2011-12 to 24 per cent in 2014. During the same period, the number of people who were not engaged in gainful employment increased from 26.5 per cent to 39.3 per cent of the labor force; among women, the rate increased from 42.4 per cent to 49.8 per cent. Those who manage to find work have to provide for a large number of dependents, with 47 per cent of the population under the age of fifteen.

The American University of Afghanistan Survey of October 2016 78 percent of the respondents believe that is that the private sector has failed to deliver jobs and that privatization and free trade has killed small local businesses while protecting larger, politically important businesses.

The theory of contestable markets can guide policy makers to design policies to deal with the job creation dilemma. Instead of focusing on the number of firms competing *in* a market. Contestable market theory concentrates on what stops firms from successfully competing *for* the market. Contestable market theory recognizes that for there to be dynamic benefits of competition, it must be relatively easy for new and more efficient firms to enter a market and for older less efficient ones to be forced to upgrade or leave. The gains from competition are thus not simply that prices will be kept as low as possible for consumers, important as that is in low–income countries; they also include the creation of opportunities for new firms, including small businesses, to enter markets and to grow, create new jobs, and the pressure on existing firms to innovate, by which we have to think of introducing new products and services and new ways to manage the business better.

The construction industry is a critical player in transforming government spending from cash to tangible public investments. It is the construction industry that delivers the roads, rails, bridges, ports, dams, airports and housing that are critical ingredients of a modern economy. In addition to delivering critical infrastructure the construction industry does do by creating jobs at scale because the industry is labor intensive. However, if the construction is not contestable but dominated by a few large international firms with small local firms locked out then the impact of government spending will be muted at the national level and totally absent in local economies.

Contestability is absent in Afghanistan. According to World Bank, Afghanistan ranks 177th in terms of regulation quality and efficiency for investment, with no improvements during 2015. The number of new firm registrations in 2015 remains well below that of 2012-13. This shows the difficulties in launching new businesses in Afghanistan. Establishing a National Competition Authority with a mandate to to take concrete steps to encourage contestability can reverse this alarming trend.

The same logic applies to the banking sector. Competition in the banking industry matters for a number of reasons. As in other industries, the degree of competition in banking matters for the efficiency of production of financial services, the quality of financial products and the degree of innovation in the sector.

Banking markets are already moving towards greater contestability. Digital technology has had the effect of lowering entry barriers into some sub-markets in the banking industry such as mobile money payments and cross-border transfers. Mobile money, which generally refers to the broad set of financial services primarily accessed via mobile devices, is one area of particular promise. Of the 2.5 billion individuals worldwide without access to formal financial services, an estimated 1 billion have access to a mobile phone. This creates a unique opportunity to provide basic mechanisms for savings, credit, insurance, payments, and transfers to the worlds poor.

Modern digital technology has lowered the marginal cost of transactions, has made distance and location increasingly less significant, has lowered consumer search costs, has increased the availability of information, and has lowered the cost of price discovery. It has also raised transparency which has lowered search costs for consumers and raised the potential for consumers to make rational choices between alternative offerings by different banks.

A contestable banking sector has the potential to better serve the needs of low-income economies. However, some caution is required when promoting contestability in financial markets.Not only are many of the relationships and tradeoffs among competition, financial system performance, access to financing, stability, and finally growth, complex from a theoretical perspective, but empirical evidence on competition in the financial sector has been scarce and to the extent available often not (yet) clear. What is evident from theory and empirics, however, is that these tradeoffs mean that it is not sufficient to analyze competitiveness from a narrow concept alone or focus on one effect only.

One has to consider competition as part of a broad set of objectives, including financial sector efficiency, access to financial services for various segments of users, and systemic financial sector stability, and consider possible tradeoffs among these objectives. And since competition depends on several factors, one has to consider a broad set of policy tools when trying to increase competition in the financial sector.

3. The Correlated Random Coefficient Panel Data Model.

In this section I motivate my choice of the correlated random coefficient (CRC) model. The CRC panel data model lies in between a pooled model with or without individual specific dummies and a model with time varying coefficients. The dummy variables in the pooled model are assumed to be fixed (fixed effects models) or random (random effects models). In these models the slope coefficients are assumed to be equal. The homogenity of the slope coefficents is an unreasonable assumption in a cross-country sample.

If heterogeneity between countries is viewed as pervasive, one can simply forsake pooling and apply individual time series to each state. Alternatively, if one believes that the long-run response is best captured by cross-sectional variation, a between-country regression approach can be employed. Yet pure cross-section studies cannot control for country-specific effects, whereas pure time-series models cannot control for unobservable shocks occurring over time

3.1. Unobserved Heterogeneity

Consider the following model

$$Y_{it} = X'_{it}\beta + \gamma Z_{it} + \epsilon_{it} \qquad \text{where } \epsilon_{it} = \alpha_i + \xi_{it} \tag{1}$$

$$Z_{it} = X'_{it}\lambda + \eta_{it} \qquad \text{where } \eta_{it} = \theta_{it} + \omega_{it}, \tag{2}$$

where Y is output in country i in year t, X_i is a vector of observed characteristics, Z_{it} is a variable measuring government spending , and $epsilon_{it}$ and η_{it} are unobservable determinants of the output of the country performance and the use of fiscal policy respectively . It is assumed that that the unobservable determinants of Y_{it} and Z_{it} consist of time -invariant country fixed effects α_i and θ_i and time-variant unobserved shocks ξ_{it} and ω_{it}. The lattter are assumed to be normally distributed with mean zero and variance σ^2_{ξ} and σ^2_{ω}.

The coefficient γ is the true effect of government spending on output(the multiplier). From Equations (1) and (2) it is trivial to see that in order to obtain consistent estimates , the least sqyuares estimator requires that $E[\epsilon_{it}\eta_{it}] = 0$. If there was random assignment of different magnitudes of government spending to different countries it woudl be possible to estimate γ from cross-section data. In observational data , such random assignment is not possible. If there are unobserved country fixed effects –captured by α_i and θi in equations (1) and (2)—that covary with Y_{it} and Z_{it}, crosse-sectional estimates of γ suffer from omitted variable bias.

Panel data provides a solution to the omitted variable bias. First differencing th data removes the country fixed effects α_i and θ_i. After first differencing the model described by equations (1) and (2) can be written as

$$\Delta Y_{it} = \Delta X_{it}'\beta + \gamma \Delta Z_{it} + \Delta \epsilon_{it} \qquad \text{where } \epsilon_{it} = \alpha_i + \xi_{it}, \tag{3}$$

$$\Delta Z_{it} = \Delta X_{it}'\lambda + \Delta \eta_{it} \qquad \text{where } \eta_{it} = \theta_{it} + \omega_{it}, \tag{4}$$

Assuming that $E[\Delta \epsilon_{it} \Delta \eta_{it}] = 0$, then estimating equation (3) provides consistent estimates of γ.

3.2. *Endogeneity*

An additional problem arises because government spending is likley to be endogenous. Transitory shocks–captured in equations (1) and (2) by ξ_{it} and ω_{it}– that are correlated with both Y_{it} and Z_{it} could lead to inconsistent estimates of γ.

Suppose there is an instrumental variable V_{it} available that causes changes in government spending without having a direct effect on output. The system of equations (3) and (4) could then be written as

$$\Delta Y_{it} = \Delta X_{it}'\beta + \gamma \Delta Z_{it} + \Delta \epsilon_{it,} \Delta Z_{it} = \Delta X_{it}'\lambda + V_{it}\Delta + \Delta \eta_{it} \tag{5}$$

respectively, Two stage-least-squares (2SLS) or generalk method of momemts (GMM) estimats of equations (5) and (6) provide consistent estimats of the effect of government spending on output if the instrument V_{it} satisfies two conditions. First V_{it} has to be partially correlated with Z_{it} in equation (6) , such that $\delta \neq 0$. Second V_{it} must be uncorrelated with unobserved transitory shocks to output , that is $E[it\epsilon_{it}] = 0$.

It is useful to think of the decision to increase government spending as the outcome of some optimal decision process. Clearly in that case the fiscal authorities will only increase government spending if the expectd benefits are greater than or equal to the costs. Because of this optimal decision process the sample of countries at any one time that increase government spending is not random.

Then it follows that the multiplier γ that is estimated based onthe models described above measures the *average* multipiler for all countries in the sample if the "supposed benefits and costs" of government spending ' are identical across countries. However, if the response of output to spending is heterogeneous, the estimated multiplier are likely to be different from the average multiplier.

The random coefficient model differs from equation (3) and (4) by a random slope coefficient γ_i:

$$\Delta Y_{it} = \Delta X_{it}'\beta + \gamma \Delta Z_{it} + \Delta \epsilon_{it,} \tag{6}$$

$$= \Delta X_{it}'\beta + \overline{\alpha} + \overline{\gamma}\Delta Z_{it} + (\alpha_i - \overline{\alpha}) + (\gamma_i - \overline{\gamma}\Delta Z_{it} + \Delta \xi_{it}, \tag{7}$$

and

$$\Delta Z_{it} = \Delta X_{it}'\lambda + V_{it}\delta + \delta\eta_{it}, \tag{8}$$

where $\overline{\alpha}$ and $\overline{\gamma}$ denote the means of α_i and γ_i respectively, and where $E[\Delta Z_{it}\Delta\xi_{it} = 0]$.

Assume that the instruments V_{it} satisfy the conditions

$$E[\alpha_i - \overline{\alpha}|V_{it}] = 0 \tag{A1}$$

$$E[\gamma_i - \overline{\gamma}|V_{it}] = 0 \tag{9}$$

and that

$$E[\Delta\xi_{it}|\Delta Z_{it}, V_{it}] = 0, E[\nu_{it}|V_{it}] = 0 \tag{A2}$$

$$E[\alpha_i - \overline{\alpha}|\Delta Z_{it} V_{it}] = \phi_{0z}\Delta Z_{it} + \phi_{0V} V_{it}, \tag{10}$$

$$E[\gamma_i - \overline{\gamma}|\Delta Z_{it} V_{it}] = \phi_{1z}\Delta Z_{it} + \phi_{1V} V_{it}. \tag{11}$$

Assumption (A2) strengthens the usual IV orthogonality conditions . Assumptions (A3) and (A4) require the conditional expectations of α and γ to be linear in ΔZ_{it} and V_{it}.

From Assumptions (A1) to (A4) it can be shown thatg $E[\alpha_i - \overline{\alpha}|\Delta Z_{it}, V_{it}] = \phi_{0Z}\eta_{it}$ and $E[\gamma_i - \overline{\gamma}|\Delta Z_{it}, V_{it}] = \phi_{1Z}\eta_{it}$. Using these relationships, the conditional expectation of ΔY_{it} can be written as

$$E[\Delta Y_{it}|\Delta Z_{it}, V_{it}, X_{it}] = \Delta X_{it}'\beta + \overline{\alpha} + \overline{\gamma}\Delta Z_{it} + \phi_{0z}\eta_{it}|\phi_{1z}\eta_{it}\Delta Z_{it}. \tag{12}$$

Following Garen (1984), consistent estimates of the average multiplier $\overline{\gamma}$ can be obtained by the *control function estimator*

$$\Delta Y_{it} = \Delta X_{it}'\beta + \overline{\alpha} + \overline{\gamma}\Delta Z_{it} + \phi_{0z}\eta_{it} + \phi_{1z}\hat{\eta}_{it}\Delta Z_{it}. + \nu_{it}, \tag{13}$$

where $\hat{\eta}_{it}$ are the estimated residuals from the first stage equation(8). Note that equation (10) diffres from a 2SLS estimator by the term $\phi_{1z}\hat{\eta}_{it}\Delta Z_{it}$ which controls for heterogeneity. Note further that the coefficients ϕ_{0Z} and ϕ_{1z} permits the anlysisof whether there is omitted variable bias. The coefficients $\phi_{0z} = Cov(\alpha_i, \eta_{it})/Var(\eta_{it})$ provides a measure of of the importance of ommitted variable bias and $\phi_{1z} = Cov(\gamma_i, \eta_{it})/Var(\eta_{it})$ measures the importance of heterogeneity in the average multiplier.

4. GMM-IV Estimation

The simplest way to estimate the multiplier is to regress the real GDP growth rate on the change in government spending by type of spending normalized by the GDP lag, so that the coefficient can be interpreted as a change in real GDP, in dollars, due to a one-dollar increase in government spending (a classic definition of the multiplier). This approach also converts data from multiple countries and periods to comparable units. Extending the methodology to a multicountry panel, we include time and country dummies, as well as other controls that may affect the size of the multiplier. The exact specification is as follows:

$$\frac{\Delta y_{it}}{y_{i,t-1}} = c + \alpha_i + m_t + \beta\left(\frac{\Delta G_{ijt}}{y_{i,t-1}}\right) + \phi\left(\left(\sum_j \frac{\Delta G_{ijt}}{y_{i,t-1}}\right) - \frac{\Delta G_{ijt}}{y_{i,t-1}}\right) + \boldsymbol{\gamma\prime X_{it}} + \epsilon_{it}, \tag{14}$$

where i is country, j is type of government spending by function and t is year, y_{it} is country i's real GDP in year t,G_{ijt} is the corresponding type of governments spending, X_{it} is a vector of controls with coefficients γ, c is a constant, α_i andβ_t are country and year fixed effects, respectively, and ϵ_{it} is the error term. The estimate $\hat{\beta}$ is the fiscal multiplier and ϕ is is the fiscal multiplier for the total of all other types of government spending .

In order to estimate a multiplier that is contingent on the level of another variable consider:

$$\frac{\Delta y_{it}}{y_{i,t-1}} = c + \alpha_i + m_t + \beta Index + \beta^x\left(\frac{\Delta G_{ijt}}{y_{i,t-1}}\right) \star Index + \phi\left(\left(\sum_j \frac{\Delta G_{ijt}}{y_{i,t-1}}\right) - \frac{\Delta G_{ijt}}{y_{i,t-1}}\right) + \boldsymbol{\gamma\prime X_{it}} + \epsilon_{it}, \tag{15}$$

where $Index$ is either absorptive capacity or contestability.Now the multiplier is contingent on the level of x for country i at time t and the multiplier is now given by

$$\beta_{it} = \beta + \beta^x \star x_{it}.$$

4.1. GMM-IV Estimation Results

In this section I report estimates of the government spending multiplier using a panel data fixed-effects GMM instrumental variables strategy. One table for each funcational category of the budget. All specifications include country and year fixed-effects. In the basic specfication, I use heteroscedasticity and autocorrelation (HAC) robust standard errors for inference and allow for a bandwidth of up to 2 lags for autocorrelation robust inference. I select the control variables and the instrumental variables intuitively. I follow Kitsiso and Patnam (2016) and use an instrument that exploits cross-country differences in fuel subsidies schemes that induce variation in government expenditures when exposed to fluctuations in oil prices. The logic behind this instrumental variable is that governments in many countries adopt subsidy policies with respect to fuel pricing to support fuel consumption and insulate consumers against global oil price fluctuations. Identification makes use of the fact that an upward oil price shock sharply increases government spending in high fuel subsidy countries relative to countries that do not subsidize fuel consumption as much. Since fuel subsidizing policies are endogenously chosen by governments, potentially in response to changing oil prices, this instrument control directly for the effect of the fuel subsidy regime and global oil price changes on output growth.

In the first, column of Table (10) I present the FE-OLS estimation results. The FE-OLS estimate of the aggregate government spending multiplier is 0.65, which is statistically significantly different from zero at the five percent level. The second column shows the estimates of the first-stage effects that the suggested instrument has on the change of total government consumption.

Using this interaction term as an instrument for the changes in government spending, I present the two-stage least squares (2SLS) estimates of the government spending multiplier in the third column of Table 2. The first-stage F-statistic is 13.1 and, therefore, exceeds the Staiger and Stock (1997) rule-of-thumb threshold of 10 below which instruments are considered weak. The point estimate of the government spending multiplier in our baseline 2SLS specification is 0.681, which is significant at the 5 percent significance level and well above the OLS estimate of column 1.

Column 4, present results from an alternative control function strategy developed by (Garen, 1984). Given the linear conditional expectations restrictions, this specification provides a simple test for the direction and magnitude of the heterogeneity bias. Column 4 of Table 2 reports three findings. Firstly, consistent with the CRC and FE-IV results, I find that the control function approach yields estimates for the average multiplier that are much higher than the OLS. Second, the estimated coefficient of the first control function,λG , is negative and highly significant. This implies that the omitted variables bias in the conventional FE-OLS estimate is non-negligible. The negative sign suggests that there are time-varying unobservables that, while positively correlated with government spending growth, are negatively correlated with GDP growth. An example of such an unobservable is the counter-cyclical nature of fiscal policy.

Third, I find that the coefficient estimate on the selection bias control function, ϕG is also negative and highly significant. This means that the negative effect of the time-varying unobservables is larger at higher levels of government spending growth.

Now I turn to focus on the interaction terms between spending variables and absorptive capacity levels of each country. Using the median of the absorptive capacity level as a cutoff, the total of 30 countries are divided into ones with high– and low-absorptive capacity. Estimates are reported in Tables 14-22.

5. Bayesian Iterative Shrinkage Estimator

The previous multipliers are averages across all 36 countries in our sample. However, our main interest is in obtaining country specific multipliers. To do so we use a Bayesian Shrinkage estimator. Shinkage estimators constitute a compromise between the homogeneous estimators that restrict at least the slope to be uniform across different cross-sections and the heterogeneous estimators that allow the parameter sets to vary completely between every cross–section.

Maddala, Trost, Li, and Joutz (1997) applied classical, empirical Bayes and Bayesian procedures to the problem of estimating short-run and long-run elasticities of residential 19 demand for electricity and natural gas in the U.S. for 49 states over 21 years (1970–1990). Since the elasticity estimates for each state were the ultimate goal of their study they were faced with three alternatives. The first is to use individual time series regressions for each state. These gave bad results, were hard to interpret, and had several wrong signs. The second option was to pool the data and use panel data estimators. Although the pooled estimates gave the right signs and were more reasonable, Maddala, Trost, Li, and Joutz (1997) argued that these estimates were not valid because the hypothesis of homogeneity of the coefficients was rejected. The third option, which they recommended, was to allow for some (but not complete) heterogeneity or (homogeneity). This approach lead them to their preferred shrinkage estimator which gave them more reasonable parameter estimates. I follow their approach to extract country specific multipliers from the panel data.

For expsoitional clarity consider the following cross–section regression

$$Y_i = X_i\beta_i + u_i for i = 1, 2, \ldots, N. \tag{16}$$

where β_i is the regression parameter with dimension K.Let y_i denote real GDP growth. For each $y_i, t = 1, 2, \ldots, T$, X_i is a set of covariates, including government spending. The traditional approach to estimating regression coefficients β_i is with either pooled cross-section or with panel data is a dichotomy of either estimating β_i from the data on the i^{th} cross-section unit or from the pooled sample. Maddala (1991) has shown that shrinking each individual βi from the i^{th} cross-section towards the weighted average $\overline{\beta}_W$ proves to be the best estimator compared to the cross-section, panel or pooled estimators.

Assume that

$$y_i \sim N(X_i\beta_i, V_i) \tag{17}$$

in which interest is in the special case that $V_i = \sigma_i^2 I$.

The shrinkage–estimator discussed in Smith (1973) and Maddala (1991) is given as

$$\beta_i^\star = \left(\frac{1}{s_1^2}X_i'X_i + \Sigma^{\star-1}\right)^{-1}\left(\frac{1}{s_1^2}X_i'X_i\widehat{\beta}_i + \Sigma^{\star-1}\widehat{\beta}_W\right)^{-1} \tag{18}$$

where

$$s_i^2 = \frac{1}{T+2}(y_i X_i \beta_i^\star)'(y_i X_i \beta_i^\star) \tag{19}$$

and

$$\Sigma^\star = \frac{1}{N-K-1}\sum(\beta_i^\star - \widehat{\beta}_W)(\beta_i^\star - \widehat{\beta}_W)' \tag{20}$$

Further, $\beta_i^\star$ is the OLS estimator based on each separate cross-section unit, i.e., $\widehat{\beta}_i = (X_i X_i)^{-1} X_i' y_i$. Note that$\widehat{}_W = N^{-1}\beta_i^\star$ is the simple average of the shrinkage estimates. Equation (20) also shows that $\beta_i^\star$ is a weighted average of the OLS estimators $\widehat{\beta}_i$ and an estimator for the prior mean $\widehat{\beta}_W$ with the weights inversely proportional to the variances.

In practice, (19) and (20) are estimated as

$$s_i^2 = \frac{1}{T+2+\nu_i}\left(\nu_i\lambda_i + (y_i + X_i\beta_i^\star)'(y_i + X_i\beta_i^\star)\right) \tag{21}$$

and

$$\sum^\star = \frac{1}{N-K-1+\delta}\left(R + \sum(\beta_i^\star - \widehat{\beta_W})(\beta_i^\star - \widehat{\beta_W})'\right) \tag{22}$$

Where $\nu_i\lambda_i, R$ and δ are parameters arising from prior specifications. Approximations to vague priors are obtained by setting $\nu_i = 0, \delta = 1, R$ to be a diagonal matrix with small positive entries (e.g., 0.001).

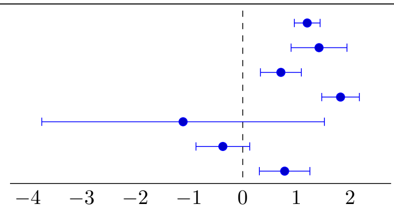
5.1. Discussion

For brevity I summarize the estimated multipliers in a forest plot. The Bayesian Shronkage estimates of average conditional functional multipliers vary from -1.11 for economic affairs to 1.82 for social protection. The total government spending multiplier is 0.78 markedly different from estimates of 0 to 0.5 in previous studies.

What are the policy implications of the estimated multipliers for policymakers in low–income? The results shows that social protection is the largest multiplier with a value of 1.82 . Considering social protection in isolation this is an important finding for low-income countries . It means that government spending on social protection is expansionary. In a resource constrained environment where decisions have to be made as to where to increase or to reduce spending it is imperative to maintain and if possible increase spending on social protection.

Table 5: **Estimates of the Conditional Functional Multiplier for Afghanistan.**

Types of Government Spending	$\hat{\beta}$	95% CI
Health	1.20	(+0.28 to +1.44)
Education	1.42	(+0.01 to +1.94)
Defence	0.71	(+0.10 to +1.09)
Social Protection	1.82	(+1.40 to +2.17)
Economic Affairs	−1.11	(+0.18 to +1.52)
General Public Services	−0.37	(+0.03 to +0.13)
Total Government Spending	0.78	(+0.35 to +1.25)



[a] Functional multipliers are estimated by 2SLS-Bayesian Iterative Shrinkage with bootstrap confidence intervals. If a 95% confidence interval crosses 0 that indicates a lack of statistical significance. This key crossing point is the vertical line, often referred to as the 'no effect' line.

The estimated multiplier on social protection of 1.82 is solidly in line with theoretical work by by Oh and Reis (2012) which explains how "well targeted transfers can have an expansionary effects on output. The authors show that transfers can change marginal incentives by changing relative prices: Subsidizing productive assets to rural families below poverty line is one such example where transfers increase the marginal incentive of the agent to acquire productive capital. An increase in marginal reward will spur economic activity while a decrease in marginal reward by the way of less return to working or saving will further dampen output and employment. Woodford (1990) also shows that transfer spending can be expansionary if it alleviates liquidity constraints which results in higher investment and output.

Education (1.48), followed by health (1.20) are the next two largest multipliers. Taken together with the multiplier on social protection the size of these estimators demonstrates the important role that social protection programs–for example through cash transfers –can have on output and poverty reduction.

Qualitative fieldwork from cash transfer programs in Lesotho, Ghana, Kenya and Zimbabwe found that while in all cases the cash transfer programs function primarily as a safety net, in the latter three countries they have also increased investment in household economic activities, in some cases particularly for female–headed households. In all contexts the programs were found to increase social capital and allow beneficiaries to "re-enter" existing social networks, and/or to strengthen informal safety nets and risk-sharing arrangements. In the case of Ghana, these results were confirmed by analysis of impact evaluation data, Handa et al. (2013). Moreover, in all four countries the cash transfer programs allowed households to be seen as more financially trustworthy, to reduce debt levels and increase credit worthiness results confirmed by experimental and quasi-experimental impact evaluation studies in both Ghana and Zambia. In many cases, however, households remain risk averse and reluctant to take advantage of increased access to credit.

The key message is that investments in health and education induced by cash transfer programs generate both short and long–term economic benefits through improvements in human capital, which lead to an increase in labor productivity and employability. However, the large size of the multipliers that is estimated in Asea (2016) suggests there is good reason to believe that cash transfer programs also influence the productive dimension of beneficiary households.

The livelihoods of most beneficiaries are predominantly based on subsistence agriculture and rural labor markets, and will continue to be so for the foreseeable future. The exit path from poverty is not necessarily the formal (or informal) labor market, but self–employment generated by beneficiary households themselves, whether inside or outside agriculture. Moreover, most beneficiaries live in places where markets for financial services (such as credit and insurance), labor, goods and inputs are lacking or do not function well. In this context, when cash transfers are provided in a regular and predictable fashion, they can help households to overcome credit constraints and manage risk. This, in turn, can increase productive investment, increase access to markets and stimulate local economies.

Cash transfers can thus potentially serve as an important complement to a broader rural development agenda, including a pro-poor growth strategy focusing on agriculture. Cash transfers can serve not just as social protection but also as a means of promoting farm and household-level production gains. This means that cash transfers function as part of both tracks of the twin track approach reducing hunger and vulnerability immediately, while at the same time facilitating household level investment in productive activitie

6. Robustness

How robust are the GMM-IV estimates?

6.1. Standard Errors

Estimates are often sensitive to the type of clustering.To evaluate the robustness of the estimates to standard errors I use various standard error correction techniques to derive inference. I cluster standard errors in four different ways: on both country and year identifiers; accounting for potential cross-sectional spatial dependence; accounting for potential cross-sectional dependence of an unknown form as per Driscooll-Kray; weak instrument robust confidence intervals. I also report weak instrument robust confidence intervals.

Panel A of Table 7 in the online Appendix reports our results for this exercise. All estimates are based on the specification reported in column 5 of Table 6 in the online Appendix. I present both 90% and 95% confidence intervals for each result. Column 1 clusters standard errors on both country and year identifiers. Our main result remains significant at the 10% level, despite that clustering by country and year increases standard errors by a slight margin. There is probably little to be gained from clustering on these units, given that we include country and year fixed-effects in our specification which tend to absorb the majority of the within-country and within-time heterogeneity. Conditional on fixed-effects, a more serious threat to our inference approach

6.2. Influential Observations and Outliers

I consider whether outliers might bias the results.The most important source of outliers is likely to be the disaggregated public spending series. The series were constructed by hand and despite the best efforts to construct the consistent series across countries some countries had gaps. I filled in these gaps by referring to reports by the fiscal authorities. Given this possibility, I first examine if there are any unusual outliers in the respective spending series.

I use two measures of leverage to drop outliers, Cook's Distance and DFFITS (Belsley, Kuh, and Welsch, 1980). Both statistics measure how much an observation influences the model as a whole. While Cook's distance measures the aggregate change in the estimated coefficients when each observation is left out of the estimation, the DFFITS statistic measures the change in the predicted value for each observation when that observation is left out of the regression. Using both techniques, we find that our IV results decrease in magnitude by a small amount but are still positive, significant and greater than one. For both methods, the first-stage F-statistic reduces slightly but remains above the Staiger and Stock (1997) rule of 10.

6.3. Different definitions of weak and superior Absorptive Capacity

Next I experiment with different cut-offs by which to categorize weak absoprtive capacity from superior absorptive capacity. Instead of the median value as a cut-off point, I now change it to the lower-third (33 percentile), implying that only governments with particularly low absorptive capacity are now classi

ed as weak. Table 7 in the online appendix shows that the estimates are slightly weakened by this change.

6.4. Alternative Measures of State Capacity

I was curious to see whether the State Antiquty index was indeed picking up the notion of state capacity as intended. I considered two other popular indicators of state capacity: a measure of contract intensive money (CIM) and the measure of bureaucratic quality produced by the Political Risk Services (PRS). CIM is the amount of money that requires "contract enforcement, regulation, or sophisticated information gathering" (Hanson and Sigman 2011) and the measure employed here is from Souva, Smith and Rowan (2008). The ability of a state to enforce contracts is thought to capture not only the sophistication of the administration, but also the level of corruption, and commitment to enforcing rule of law. The PRS measure of bureaucratic quality from the International Country Risk Guide (ICRG) is an aggregated score based on expert assessments of 3 dimensions: (1) regular, meritocratic recruitment and advancement processes, (2) insulation from political pressure, and (3) the ability to provide services during government changes (Knack, 2001). The measure ranges from 0 or low quality to 6 high quality.

7. Post-Double LASSO Estimator of Conditional Functional Multipliers

In this section I use the post-double LASSO estimator of Belloni *et al.* (2013) to determine whether the estimated relationship between spending and output is causal and not simply a correlation. This is a higher bar than the robustness tests in the previous section.

LASSO estimators use machine learning to select control variables to be included in an empirical model. This is arguably one of the most important steps in any empirical reserach. Model selection—choosing the correct regressors to include in an empirical model–is critical step in any empirical research. Including too many covariates increases the variance of the model, and taking fewer covariates than needed results in inconsistent estimates. With the explosion in computing power, contemporary researchers are faced with high-dimensional datasets. From weather variables, satellite images of night lights, to latitude and longtitude, other spatial geographic such as distances, political variable, legal and the list goes on. Add to this list squared and cubic terms products of variables and the list can grow into the thousands.

When there are more covariates than observations—high-dimensional data—it forces researchers to search for a model that is simultaneously parsimonious and adequately flexible. Which control variables should be included in the model? Which controls can be excluded from the analysis without introducing omitted variable bias? How sensitive are the estimated effects to these specification decisions?

The least absolute shrinkage and selection operator (Lasso) (Tibshirani 1996) has become a very popular method for simultaneous model selection and parameter estimation. Among the Lasso's main advantages are the combination of prediction accuracy and the parsimony of models built. The Lasso-type estimator outperforms simple application of parameter estimation methods (as, e.g., ordinary least squares or method of moments) since it shrinks the coefficients of insignificant regressors towards zero. Hence, the resulting models concentrate on the strongest effects and the total accuracy of the model forecast is increased. In addition, the Lasso solutions are more stable than other subset selection techniques based on the information criteria and stepwise strategies as, e.g., thhe (RETINA) analyzed by Perez-Amaral et al. (2003).

Another important advantage of the Lasso is its computational feasibility. Since its computational cost hardly exceeds the complexity of one linear regression (Efron et al. 2004), it is more attractive in comparison to classical model selection strategies that involve more intensive combinatorial search. However, the Lasso-estimator has some limitations. In particular, inconsistent results are obtained for highly correlated regressors which is very common in macroeconomic times eriers such as this one.

In a series of papers, Belloni *et al.* (2013a) and Belloni *et al.* (2012) propose techniques for inference on treatment effects in linear, instrumental variables, and logistic regression problems. These techniques incorporate multiple stages of variable selection with data-driven penalties that ensure the relevant controls are included in the econometric model before performing inference in an unpenalized postselection model. By focusing on inference for a predefined, fixed-dimensional, subset of coefficients, the selected models represent a desparsified data generating process, with inference results from van de Geer et al. (2014) providing uniformly valid confidence intervals.

I follow the steps outlined in Belloni (2013) *et al*:

1. In the first step,I select a set of control variables that are useful for predicting the government spending. This step helps to insure validity of post-model-selection-inference by finding control variables that are strongly related to government spending and thus potentially important confounding factors.

   I select high-dimensional controls from a wide variety of sources. These include higher order terms and interactions of the control variables with such higher order terms. In addition, I include country initial conditions and initial differences and within–country averages into the vector of controls. I include levels and interactions with rainfall, temperature, legal constraints and bureaucratic capacity. I allow for quadratic trends and interactions of the quadratic trend with controls. At the end of this process I end up 178 controls in addition to the 30 time effects.[4]

2. In the second step,I select additional variables by selecting control variables that predict output growth. This step helps to insure that we have captured important elements in the equation of interest, ideally helping keep the residual variance small, as well as providing an additional chance to find important confounds.

3. In the final step,I estimate the treatment effect(γ) that is of interest (i.e. the multiplier) by the linear regression of GDP growth on govenment spending (and its six functional components) and the union of the set of variables selected in the two variable selection steps.

The results are displayed in Table (20). Estimates of the causal effect of government spending on output obtained by searching for confounding factors among the set of 178 potential controls are given in the second and third columns of Table 20. Each of these estimates is obtained from the least squares regression of government spending on output and the six controls selected by the double-post-Lasso procedure. All of these estimates of the multiplier are quite precise and only slightly larger than the estimates obtained in the GMM-IV approach, part from the multiplier on general services which turns negative and loses significance. Esti-

[4]Details of the 178 controls are in provided in the Supplementary Appendix.

mates in the third column do not change much when we add the original intuitively selected controls. This demonstrates that the intuitively selected controls were sound choices.

8. Shrinkage Estimators

One of the limitations of the CRC panel data model is that the multipliers are averages over the countries in the sample. Shrinkage estimators can be used to estimate individual country multipliers. Maddala *et al.*(1994) argues that Shrinkage estimators are superior to either the individual state (heterogeneous) estimates or the pooled (homogeneous) estimates.

In the shrinkage approach, one shrinks the individual estimates towards the pooled estimate using weights depending on their corresponding variance-covariance matrices.

We explore seven different shrinkage estimator for the coefficient γ (the conditional functional multiplier) in our base specification. Results of the shrinkage estimator are displayed in Table (21). There appears to be a strong relationship between the size of the multiplier and absorptive capacity. The stronger the abosrptive capacity the larger the multiplier. This holds true for all functional components of spending as well as for aggregate government spending.

9. Conclusion

Multipliers matter. Precise estimates of conditional functional multipliers are critical for the conduct of fiscal policy. Yet there was little solid evdence on the magnitude of multipliers in low-income countries. By disaggregating spending into its functional components, carefuly accounting for cross-country heterogeneity and conditioning on the absorptive capacity of low-income I estimate conditional functional multipliers that vary from 0.37 for general services to 3.2 for health spending.This is much larger than the few published estimates for low-income countries which are are in the range of 0 to 0.5 (Kraay, 2002/14, Ilzetski et. al. (2011).

The key novelty in this paper is to operationalize the concept of absorptive capacity so that it can be used in an empirical model. I do so by by using state antiquity as a proxy for absorptive capacity, Brockette *et al.* (2012). Absorptive capacity is a key characteristic of low-income countries that has important implications for how output responds to spending. I am not the first to recognize the importance of structural charecteristics of a country when estimating multipliers. Ilzetzki et al (2011) find that the multiplier depends critically on the degree of development, the monetary policy framework and the degree of openness. Their estimate of the multiplier is not significantly different from zero for countries with a flexible exchange rate and they find the multiplier is smaller for more open economies.

Methodologically I illustrate the importance of determining whether estimates from the GMM-IV model are causal. I show how this can be done using the post-Double LASSO estimator of Belloni *et al.* (2013). This kind of rigorous analysis is important given the huge increase in high-dimensional data. Selecting control variables and instrumental variables intuitively is fraught with danger. Estimated relationships can be shown to be spurious when subjected to the Post-Double LASSO principled procedure for the selection of control variables. This new and powerul proedure draws on recent developments in statistical theory and machine learning and has wide application in all areas of applied economics.

References

Acosta-Ormaechea, S. and A. Morozumi 2013, "Can a government enhance long– run growth through changes in the composition of public expenditure?" IMF Working Paper 13/162.

Afonso, A., Alegre, J.G., 2008."Economic Growth and Budgetary Components. A Panel Assessment for the EU. " ECN Working Paper 848.

Afonso, A., Ebert, W., Schuknecht, L., Thöne, M., 2005. "Quality of Public Finances and Growth. " ECB Working Paper 438.

Afonso, A., Furceri, D., 2010. "Government Size, Composition, Volatility and Growth." *European Journal of Political Economy* 26, 517–532.

Auerbach, Alan J., and Yuriy Gorodnichenko, 2012,"Measuring the Output Responses to Fiscal Policy," *American Economic Journal: Economic Policy*, Vol. 4, No. 2, pp. 1–27.

Barro, Robert J., 1990,"Government Spending in a Simple Model of Endogeneous Growth," *Journal of Political Economy*, Vol. 98, No. 5, pp. S103–S125.

Baum, Anja, Marcos Poplawski-Ribeiro, and Anke Weber, 2012,"Fiscal multipliers and the state of the economy," IMF Working Paper No. 12/286, (Washington: International Monetary Fund).

Belloni, Alexandre, D. Chen, V. Chernozhukov, and C. Hansen, 2012, "Sparse models and methods for optimal instruments with an application to eminent domain, " *Econometrica*, 80, 2369–2431.

Belloni, Alexandre, D. Chen, V. Chernozhukov, and C. Hansen, 2012, "Inference on treatment effects after selection amongst high-dimensional controls," *Review of Economic Studies*, 80, 2369–2431.

Bockstette, Valerie, Areendam Chanda and Louis Putterman, 2002,"States and Markets: The Advantage of an Early Start, ," *Journal of Economic Growth* 7: 347–69.

Blanchard, Olivier J., and Daniel Leigh, 2013,"Growth Forecast Errors and Fiscal Multipliers," *American Economic Review*, Vol. 103, No. 3, pp. 117–20.

Caner, Mehmet.; Xu Han, aand Yoonseok Lee , 2015, "Adaptive Elastic Net GMM Estimation with Many Invalid Moment Conditions: Simultaneous Model and Moment Selection" *Journal of Business and Economics Statistics*

Caner, M. and H.H. Zhang, 2014. " Adaptive elastic net GMM estimator, *Journal of Business and Economics Statistics*," 32, 30–47.

Chamberlain, Gary, 1982, "Multivariate Regression Models for Panel Data," *Journal of Econometrics*, Vol. 18, No. 1, pp. 5 –46.

________________, 1992,"Efficiency Bounds for Semiparametric Regression," *Econometrica*, Vol. 60, No. 3, pp. 567596.

Cheng, X. and Z. Liao 2015." Select the valid and relevant moments: An information-based LASSO for GMM with many moments," *Journal of Econometrics*, 186, 443–464.

________________, 2008, "The Reduced Form: A Simple Approach to Inference with Weak Instruments," *Economics Letters*, Vol. 100, No. 1, pp. 68 – 71.

Christiano, Lawrence, Martin Eichenbaum, and Sergio Rebelo, 2011, "When is the Government Spending Multiplier Large?" *Journal of Political Economy*, Vol. 119, No. 1, pp. 78–121.

Coady, David, Rolando Ossowski, John M. Piotrowski, Shamsuddin Tareq, Justin Tyson, and Robert Gillingham, 2010,"Petroleum Product Subsidies: Costly, Inequitable, and Rising," IMF Staff Position Note No. 10/05, (Washington: International Monetary Fund).

Coenen, Gü nter, Christopher J. Erceg, Charles Freedman, Davide Furceri, Michael Kumhof, René Lalonde, Douglas Laxton, Jesper Lindé, Annabelle Mourougane, Dirk Muir, Susanna Mursula, Carlos de Resende, John Roberts, Werner Roeger, Stephen Snudden, Mathias Trabandt, and Jan in't Veld, 2012,"Effects of Fiscal Stimulus in Structural Models," *American Economic Journal: Macroeconomics*, Vol. 4, No. 1, pp. 22–68.

Conley, T.G., 1999, "GMM Estimation with Cross Sectional Dependence," *Journal of Econometrics*, Vol. 92, No. 1, pp. 1 – 45.

Corsetti, Giancarlo, André Meier, and Gernot J. Müller, 2012,"What Determines Government Spending Multipliers?" *Economic Policy*, Vol. 27, No. 72, pp. 521–565.

Cutler, D.M., Lleras-Muney, A., 2006."Education and Health: Evaluating Theories and Evidence. National Poverty Center Working Paper Series 06-19.

Devarajan, S., V. Swaroop, and H.-f. Zou ,1996, "The composition of public expenditure and economic growth," *Journal of Monetary Economics*, 37, 313–344.

Driscoll, John C., and Aart C. Kraay, 1998, "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data," *The Review of Economics and Statistics*, Vol. 80, No. 4, pp. 549–560.

Favero, Carlo, Francesco Giavazzi, and Jacopo Perego, 2011, "Country Heterogeneityand the International Evidence on the Effects of Fiscal Policy," *IMF Economic Review*, Vol. 59, No. 4, pp. 652–682.

Garen John, 1984,"The Returns to Schooling: A Selectivity Bias Approach with a Continuous Choice Variable" *Econometrica*, 1984, vol. 52, issue 5, pages 1199–1218

Gemmell, N., Kneller, R., Sanz, I., 2011. "The Timing and Persistence of Fiscal Policy Impacts on Growth: Evidence from OECD Countries." *Economic Journal* 121, F33–F58.

Ghosh, S., Gregoriou, A., 2008."The Composition of Government Spending and Growth: Is Current or Capital Spending Better? *Oxford Economic Papers* 60, 484–516.

Gupta, Sanjeev, Benedict Clements, Emanuele Baldacci, and Carlos Mulas-Granados, 2002, "Expenditure Composition, Fiscal Adjustment, and Growth in Low-income Countries," IMF Working paper 02/77 (Washington DC).
Turnovsky, Stephen and Walter Fisher, 1995, "The Composition of Government Expenditure and Its Consequences for Macroeconomic Performance," *Journal of Economic Dynamics and Control*, vol. 19 no. 4, 747-86.

GIZ, 2012, International Fuel Prices 2010/2011, Vol. 7th ed. (Bonn and Eschborn, Germany: German International Cooperation).

Graham, Bryan S., and James L. Powell, 2012,"Identification and Estimation of Average Partial Effects in Irregular Correlated Random Coefficient Panel Data Models," *Econometrica*, Vol. 80, No. 5, pp. 2105–2152.

Heckman, James J., Sergio Urzua, and Edward Vytlacil, 2006, "Understanding Instrumental Variables in Models with Essential Heterogeneity," *The Review of Economics and Statistics*, Vol. 88, No. 3, pp. 389–432.

Hoechle, Daniel, 2007,"Robust Standard Errors for Panel Regressions with Cross Sectional Dependence," *Stata Journal*, Vol. 7, No. 3, pp. 281–312.

IEA, 2013,"Energy Prices and Taxes," Vol. 2013, No. 1, IEA, Paris.

Ilzetzki, Ethan, Enrique G. Mendoza, and Carlos A. Vé gh, 2013,"How Big (Small?) are Fiscal Multipliers?" *Journal of Monetary Economics*, Vol. 60, No. 2, pp. 239 – 254.

Kraay, Aart, 2012,"How large is the Government Spending Multiplier? Evidence from World Bank Lending," *The Quarterly Journal of Economics*, Vol. 127, No. 2, pp. 829–887.

Rajkumar, A. S. and V. Swaroop, 2008,"Public spending and outcomes: Does governance matter?" *Journal of Development Economics*, 86, 96 111

Liao, Zheng (2013). " Adaptive GMM shrinkage estimation with consistent moment selection, *Econometric Theory*, 29, 857–904.

Murtazashvili, Irina, and Jeffrey M. Wooldridge, 2008,"Fixed Effects Instrumental Variables Estimation in Correlated Random Coefficient Panel Data Models," *Journal of Econometrics*, Vol. 142, No. 1, pp. 539 — 552.

Nassif, Claudia."Afghanistan in Transition: Building the Foundations for Future Economic Growth and Stability," *Georgetown Journal of International Affairs*, vol. 14, no. 2, 2013, pp. 165–174.

Parker, Jonathan A., 2011, "On Measuring the Effects of Fiscal Policy in Recessions," *Journal of Economic Literature*, Vol. 49, No. 3, pp. 703–18.

Perez-Amaral,Teodosio Giampiero M. Gallo and Halbert White, 2003, "A Flexible Tool for Model Building: the Relevant Transformation of the Inputs Network Approach (RETINA)" *Oxford Buletin of Economics and Statistics*, 65, 0305–9049

Pesaran, M. Hashem, 2006,"Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure," *Econometrica*, Vol. 74, No. 4, pp. 967–1012.

Putterman, Louis and David Weil, 2010,"Post-1500 Population Flows and the Long Run Determinants of Economic Growth and Inequality," *Quarterly Journal of Economics* 125 (4): 1627—1682.

Staiger, Douglas, and James H. Stock, 1997,"Instrumental Variables Regression with Weak Instruments," *Econometrica*, Vol. 65, No. 3, pp. 557—586.

Tibshirano, Robert, 1996,"Regression Shrinkage and Selection via LASSO,"*Journal of the Royal Statistical Society, Series B, Methodological* 58 (1) 267–288.

Wickens, T. (2002): "Government Finance Stataistics Manual 2001 Companion Material: Classi
cation of GFSM 1986 data to the GFSM 2001 framework," International Monetary Fund.

Zou, H. 2006. "The adaptive lasso and its oracle properties, " *Journal of The American Statistical Association*, 101, 1418-1429

Table 1: HISTORICAL ORIGINS OF ABSORPTIVE CAPACITY

Country	State History	Neolithic	Ancient Cities
Afghanistan	0.70	4587	345
Bangladesh	0.63	5500	1243
Benin	0.53	3100	432
Burkina Faso	0.65	2900	421
Burundi	0.60	3500	534
Cambodia	0.66	3000	218
CAR	0.16	3000	764
Chad	0.36	3000	450
Congo, Rep.	0.53	3000	540
DR, Congo	0.63	2450	570
Ethiopia	0.92	4000	521
Eq. Guinea	0.34	3000	890
Gambia	0.52	3000	412
Ghana	0.57	3500	328
Guinea	0.49	3250	451
Guinea B.	0.32	3580	529
Jordan	0.5	10,500	247
Kenya	0.16	3,500	582
Kyrgyzstan	0.46	6,000	761
Laos	0.61	6,000	230
Liberia	0.38	3580	451
Madagascar	0.64	2,000	1745
Malawi	0.65	1,800	641
Mali	0.59	3000	498
Mauritania	0.54	3,500	471
Mozambique	0.52	1,400	481
Nepal	0.94	6,000	1763
Niger	0.69	4,000	618
Rwanda	0.79	2,500	714
Sierra Leone	0.23	2,500	256
Tajikistan	0.50	3000	491
Togo	0.31	3,100	329
Uganda	0.63	4,958	89
Yemen	0.49	3,200	481
Zambia	0.44	1,800	651
Zimbabwe	0.38	1,400	78

[a] Neolithic denotes the the number of years since the neolithic revolution which is the time at which hunter–gatherers took up plant and animal domestication.
[b] Geodesic distance measured in kilometers from current capital city to nearest ancient city. Source for Geocoded data on ancient cities is Reba, M. et al. Spatializing 6,000 years of global urbanization from 3700 BC to AD 2000. Sci. Data

Table 2: Historical Origins of Absorptive Capacity

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TABLE 1
SURVEY OF THE LITERATURE ON CONDITIONAL FISCAL MULTIPLIERS

Authors	Data	Size of Multiplier
	Estimated with structural VARs– US data	
Auerbach and Gorodnichenko(2010)	Quarterly Data[1950-2010]	0.5 at impact, as high as 2.5 in recessions, and < 0in expansions
Bilbiie (2008)	Quarterly Data[1957-2004]	0.4 until 1979 then 0.15 after 1982
Candelon and Lieb (2013)	Quarterly Data[1968-2010]	> 1in recessions and < 1 in expansions
Fazzari et al. (2012)	Quarterly Data[1967-2011]	1.5 when economy slack 1.2 when full employment
Hall (2009)	Quarterly Data[1930-2008]	0.7 to1.0 but at the zero lower bound derives a theoretical multiplier of 1.7
Kandil (2001)	Quarterly Data[1955-1996]	> 0 in recessions. Notes asymmetry, stressing that fiscal tightening results in pronounced contraction.
Monacelli and Perotti (2008)	Quarterly Data[1954-2006]	peaks at 2 then falls to 0.Multiplier is increasing in share of government purchases spent on on non-traded goods
Mountford and Uhlig (2009)	Quarterly Data(1955-2000)	0.5 at impact though < 0 in long run.Tax cuts have multiplier of 3.8
	Estmated with Panel Data Methods–Non-US data	
Afonso	15 EU Countries	Implictly < 0 Spending cuts are expansionary
Alesina and Ardana (2010)	Annual Data (1970-2007)	30 OECD countries < 1 tax cuts increase growth more than spending increases.
Alumnia and Benetrix (2010)	Annual Data (1925-1939)	27 countries. 1.2-2.5 for defense spending but only 0.13-0.43 for total government spending
Auerbach & Gorodnichenko (2012a)	Annual Data (1984-2010)	Allows for spillovers and the state of the economy in source and recipient countries increase multiplier.
Auerbach & Gorodnichenko (2012b)	Annual Data (1984-2011)	31 OECD countries multiplier is larger in recessions than during normal times or in expansions
Batini et al. (2012)	Quarterly data [1975-2010]	US, EU, and Japan multiplier is 10 times larger during recessions than during expansions
Baum et al. (2012)	Quarterly data [1966-2011]	G7 (minus Italy) 2.2 in downturns and -2.0 in expansions.
Favero et al. (2011)	Annual Data [1978-2000]	8 OECD countries multiplier is decreasing in debt and openness.
Guajardo et al. (2010)	Annual Data [1980-2009]	15 countries $> 0\%$. Finds that Fiscal consolidation reduces output.
Ilzetzki et al. (2013)	Quarterly Data (1966-2006)	44 developing countries multiplier falls with openness to trade exchange rate flxexibility, public indebtedness, and rises in level of development.
Karras (2011)	Annual Data[1951-2011]	62 countries a 10% increase in openness reducesmultiplier by more than 5%. Multipliers range from 0.6 for open to 1.5 for a closed economies
Karras (2014)	Annual Data[1970-2005]	179 countries demonstrates that openness increases the spillover effect as suggested by basic theory
Tagkalakis (2008)	Annual Data[1970-2002]	19 OECD countries Demonstrates that binding liquidity constraints increase effectiveness of fiscal policy and that fiscal policy boosts private consumption in recessions more than in expansions.

TABLE 2
SURVEY OF THE LITERATURE ON UNCONDITIONAL FISCAL MULTIPLIERS

Authors	Data	Size of Multiplier
Barro (1981)	[1889-1978] Annual US Data	Less than 1 and uses defense spending
Barro & Redlick (2011)	[1889-1978] Quarterly US data	0.54 to 0.74 uses defense spending, defense news
Blanchard & Perotti (2002)	[1947-1997] Quarterly US data	1.25 at impact 0.96 4 years
Burnside et. al. (2000)	[1947-1995] Quarterly US data	0.125 to 0.5 imputed from IRFs.
Edelberg et. al. (1999)	[1939-2006] Quarterly US data	1.6 uses defense spending, defense news.
Ellahie & Ricco (2013)	[1959-2012] Quarterly US data	0.28 state and local fiscal multipliers.
Fatas & Mihov (2001)	[1960-1997] Quarterly US data	Larger than 1.
Fisher & Peters (2010)	[1960-2008] Quarterly US data	0.6 uses defense spending.
Ramey (2011a)	[1939-2006] Quarterly US data	0.6–1.2 uses defense spending, defense news.
Perotti (2007)	[1947-2006] Quarterly non-US data	0.7 on impact and 1.2 in long-run with panel data methods
Beetsma et al. (2006)	[1980-2002] Annual non-US data	Data from 15 EU countries. 0.358 fiscal expansions leads to increase bilateral trade with panel data methods

TABLE 3
SURVEY OF THE LITERATURE ON CONDITIONAL FISCAL MULTIPLIERS

Authors	Data	Size of Multiplier
Auerbach and Gorodnichenko(2010)	[1950-2010] Quarterly US Data	0.5 at impact, as high as 2.5 in recessions, and negative in expansions
Bilbiie (2008)	(1957-2004)Quarterly US data	0.4 until 1979 then 0.15 after 1982
Candelon and Lieb (2013)	[1968-2010]Quarterly Data, US data	Positive in recessions and less than one in expansions
Fazzari et al. (2012)	[1967-2011] Quarterly US data	1.5 when there underutilization and 1.2 under full employment
Hall (2009)	([930-2008] Quarterly US data	0.7 to1.0 but, at the zero lower bound,Hall derives a theoretical multiplier of 1.7
Kandil (2001)	[1955-1996] Quarterly US data	Greater than zero in recessions. Notes asymmetry, stressing that fiscal tightening results in pronounced contraction.
Monacelli and Perotti (2008)	[1954-2006] Quarterly US data	peaks at 2 then falls to 0. Multipliers increasing in share of government purchasesspent on non-traded goods.
Mountford and Uhlig (2009)	[1955-2000] Quarterly US data	0.5 at impact though negative in long run. Tax cuts have multiplier of 3.8

[a] Sample footnote for that was generated with the deluxetable environment
[b] Another sample footnote for

TABLE 4
CLASSIFICATION OF FUNCTIONS OF GOVERNMENT (COFOG)

Code	Description	Observations
701	General Public Services	Executive and legislative organs, financial and fiscal affairs, external affairs, Public debt transactions; General and public services; Foreign economic aid;Police, Fire and Law courts R&D; public order and safety.
702	Defence	Military and civil defence; foreign aid defence.
704	Economic Affairs	General economic, commercial, and labour affairs; agriculture, forestry, Fishing, hunting, fuel and energy, mining, manufacturing, construction, transport, communication and other industries.
706	Housing	Housing and community development; Water supply, street lighting.
707	Health	Government outlays on health include expenditures on services provided to individual persons and services provided on a collective basis; Medical products, appliances, and equipment; Outpatient, hospital, and public health services
709	Education	Pre-primary, primary, secondary, post-secondary, non-tertiary, tertiary education Provision of education not definable by level; Subsidiary services to education
710	Social protection	Sickness and disability, old age, survivors, family and children, unemployment, housing, and social exclusion.

NOTE. — Governnment Financial Statistics IMF

TABLE 5
COUNTRIES IN THE SAMPLE

Country	Code	Annual Observations
Afghanistan	AFG	9
l Burkina Faso	BFA	24
Bolivia	BOL	24
Central African Republic	CAF	24
Cote d'Ivoire	CIV	24
Comoros	COM	24
Cape Verde	CV	23
Ethiopia	ETH	24
Ghana	GHA	24
Guinea	GIN	24
Gambia	GAM	24
Jordan	JOR	24
Kenya	KEN	24
Lesotho	LES	24
Morocco	MAR	24
Madagascar	MDG	24
Mali	MLI	24
Malawi	MWI	24
Niger	NIG	24
Rwanda	RWA	24
Senegal	SEN	24
Sierra Leone	SLE	24
Chad	TSC	24
Togo	TOG	24
Tunisia	TUN	24
Tanzania	TZA	24
Uganda	UGA	24
Zambia	ZMB	24

TABLE 6
ESTIMATES OF THE CONDITIONAL FISCAL MULTIPLIER ON AGGREGATE GOVERNMENT SPENDING

	OLS	Instrumental Variables		
		1st Stage	2nd Stage	Control Function
	(1) Δ GDP	(2) Δ Government Spending	(3) Δ GDP	(4) Δ GDP
Δ Government Spending	0.134**		0.681**	0.657**
	(0.134)		(0.817)	(0.638)
Lag oil price shock × gas subsidy		0.013***		
		(0.003)		
Lag gas subsidy		0.007	0.003	0.001
		(0.002)	(0.003)	(0.002)
Lag diesel subsidy		0.003	0.001	0.001
		(0.007)	(0.003)	(0.001)
ϕ_G				-0.932
				(0.134)
Joint F-Test				6.11**
Observations	705	705	705	705
Monetary Policy	Yes	Yes	Yes	Yes
Tax Rates	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
First Stage F-Stat			13.15	

NOTE. — This table reports estimates of the effect of growth in government spending on growth in GDP. The Oil Price Shock is calculated as product of the log-change of the crude oil price with the country's average ratio of net oil exports over GDP. Gas Subsidy regime takes the value 0 for countries with no subsidy (retail gasoline price above the U.S. gasoline and Brent prices), 1 for low subsidy (retail gasoline price below the U.S. gasoline price but above the Brent price) and 2 for high subsidy (retail gasoline price below the Brent price). Column 1 reports results from a FE-OLS regression. Column 2 reports the first stage of the IV regression where the dependent variable is growth in government expenditure. Column 3 reports the corresponding second stage; the dependent variable is growth in GDP. Standard errors are robust to heteroscedasticity and autocorrelation (up to 2 lags) and are reported in parentheses. Column 4 reports results from Garen's (1984) selectivity bias correction method. Standard errors are adjusted for the heteroskedasticity. * indicates significance at 10%; ** at 5%; *** at 1%.

TABLE 7
ESTIMATES OF THE CONDITIONAL FISCAL MULTIPLIER ON DEFENSE SPENDING

	OLS	Instrumental Variables		
		1st Stage	2nd Stage	Control Function
	(1) Δ GDP	(2) Δ Defense Spending	(3) Δ GDP	(4) Δ GDP
Δ Defense Spending	0.734**		1.681**	2.716**
	(0.376)		(0.78)	(0.638)
Lag oil price shock × gas subsidy		0.013***		
		(0.003)		
Lag gas subsidy		0.006	0.006	0.031
		(0.012)	(0.033)	(0.012)
Lag diesel subsidy		0.004	0.001	0.011
		(0.007)	(0.003)	(0.001)
ϕ_G				-0.832
				(0.434)
Joint F-Test				6.11**
Observations	705	705	705	705
Monetary Policy	Yes	Yes	Yes	Yes
Tax Rates	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
First Stage F-Stat			15.25	

NOTE. — This table reports estimates of the effect of growth in defense spending on growth in GDP. The Oil Price Shock is calculated as product of the log-change of the crude oil price with the country's average ratio of net oil exports over GDP. Gas Subsidy regime takes the value 0 for countries with no subsidy (retail gasoline price above the U.S. gasoline and Brent prices), 1 for low subsidy (retail gasoline price below the U.S. gasoline price but above the Brent price) and 2 for high subsidy (retail gasoline price below the Brent price). Column 1 reports results from a FE-OLS regression. Column 2 reports the first stage of the IV regression where the dependent variable is growth in government expenditure. Column 3 reports the corresponding second stage; the dependent variable is growth in GDP. Standard errors are robust to heteroscedasticity and autocorrelation (up to 2 lags) and are reported in parentheses. Column 4 reports results from Garen's (1984) selectivity bias correction method. Standard errors are adjusted for the heteroskedasticity. * indicates significance at 10%; ** at 5%; *** at 1%.

TABLE 8
ESTIMATES OF THE CONDITIONAL FISCAL MULTIPLIER ON EDUCATION

	OLS	Instrumental Variables		
		1st Stage	2nd Stage	Control Function
	(1)	(2)	(3)	(4)
	Δ GDP	Δ Education Spending	Δ GDP	Δ GDP
Δ Education	0.234**		0.486**	1.42**
	(0.08)		(0.163)	(0.471)
Lag oil price shock × gas subsidy		0.063***		
		(0.002)		
Lag gas subsidy		0.009	0.013	0.001
		(0.006)	(0.003)	(0.00)
Lag diesel subsidy		0.003	0.001	0.001
		(0.007)	(0.003)	(0.001)
ϕ_G				-0.602
				(0.134)
Joint F-Test				9.11**
Observations	705	705	705	705
Monetary Policy	Yes	Yes	Yes	Yes
Tax Rates	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
First Stage F-Stat			17.15	

NOTE. — This table reports estimates of the effect of growth in education spending on growth in GDP. The Oil Price Shock is calculated as product of the log-change of the crude oil price with the country's average ratio of net oil exports over GDP. Gas Subsidy regime takes the value 0 for countries with no subsidy (retail gasoline price above the U.S. gasoline and Brent prices), 1 for low subsidy (retail gasoline price below the U.S. gasoline price but above the Brent price) and 2 for high subsidy (retail gasoline price below the Brent price). Column 1 reports results from a FE-OLS regression. Column 2 reports the first stage of the IV regression where the dependent variable is growth in government expenditure. Column 3 reports the corresponding second stage; the dependent variable is growth in GDP. Standard errors are robust to heteroscedasticity and autocorrelation (up to 2 lags) and are reported in parentheses. Column 4 reports results from Garen's (1984) selectivity bias correction method. Standard errors are adjusted for the heteroskedasticity. * indicates significance at 10%; ** at 5%; *** at 1%.

TABLE 9
ESTIMATES OF THE CONDITIONAL FISCAL MULTIPLIER ON HEALTH

	OLS	Instrumental Variables		
		1st Stage	2nd Stage	Control Function
	(1) Δ GDP	(2) Δ Health Spending	(3) Δ GDP	(4) Δ GDP
Δ Health Spending	1.374**		0.681**	3.20**
	(0.)58		(0.227)	(1.087)
Lag oil price shock $\times$ gas subsidy		0.023***		
		(0.005)		
Lag gas subsidy		0.004	0.013	0.011
		(0.002)	(0.003)	(0.002)
Lag diesel subsidy		0.023	0.006	0.004
		(0.007)	(0.003)	(0.001)
ϕ_G				-0.832
				(0.134)
Joint F-Test				16.11**
Observations	705	705	705	705
Monetary Policy	Yes	Yes	Yes	Yes
Tax Rates	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
First Stage F-Stat			11.58	

NOTE. — This table reports estimates of the effect of growth in health spending on growth in GDP. The Oil Price Shock is calculated as product of the log-change of the crude oil price with the country's average ratio of net oil exports over GDP. Gas Subsidy regime takes the value 0 for countries with no subsidy (retail gasoline price above the U.S. gasoline and Brent prices), 1 for low subsidy (retail gasoline price below the U.S. gasoline price but above the Brent price) and 2 for high subsidy (retail gasoline price below the Brent price). Column 1 reports results from a FE-OLS regression. Column 2 reports the first stage of the IV regression where the dependent variable is growth in government expenditure. Column 3 reports the corresponding second stage; the dependent variable is growth in GDP. Standard errors are robust to heteroscedasticity and autocorrelation (up to 2 lags) and are reported in parentheses. Column 4 reports results from Garen's (1984) selectivity bias correction method. Standard errors are adjusted for the heteroskedasticity. * indicates significance at 10%; ** at 5%; *** at 1%.

TABLE 10
ESTIMATES OF THE CONDITIONAL FISCAL MULTIPLIER ON GENERAL SERVICES

	OLS	Instrumental Variables		
		1st Stage	2nd Stage	Control Function
	(1)	(2)	(3)	(4)
	Δ GDP	Δ General Services Spending	Δ GDP	Δ GDP
Δ General Services	0.014**		0.157**	0.37**
	(0.004)		(0.052)	(0.175)
Lag oil price shock $\times$ gas subsidy		0.023***		
		(0.007)		
Lag gas subsidy		0.004	0.013	0.021
		(0.002)	(0.003)	(0.002)
Lag diesel subsidy		0.023	0.031	0.051
		(0.007)	(0.003)	(0.001)
ϕ_G				-0.812
				(0.270)
Joint F-Test				8.11**
Observations	705	705	705	705
Monetary Policy	Yes	Yes	Yes	Yes
Tax Rates	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
First Stage F-Stat			14.51	

NOTE. — This table reports estimates of the effect of growth in government spending on growth in GDP. The Oil Price Shock is calculated as product of the log-change of the crude oil price with the country's average ratio of net oil exports over GDP. Gas Subsidy regime takes the value 0 for countries with no subsidy (retail gasoline price above the U.S. gasoline and Brent prices), 1 for low subsidy (retail gasoline price below the U.S. gasoline price but above the Brent price) and 2 for high subsidy (retail gasoline price below the Brent price). Column 1 reports results from a FE-OLS regression. Column 2 reports the first stage of the IV regression where the dependent variable is growth in government expenditure. Column 3 reports the corresponding second stage; the dependent variable is growth in GDP. Standard errors are robust to heteroscedasticity and autocorrelation (up to 2 lags) and are reported in parentheses. Column 4 reports results from Garen's (1984) selectivity bias correction method. Standard errors are adjusted for the heteroskedasticity. * indicates significance at 10%; ** at 5%; *** at 1%.

TABLE 11
ESTIMATES OF THE CONDITIONAL FISCAL MULTIPLIER ON SOCIAL PROTECTION

	OLS	Instrumental Variables		
		1st Stage	2nd Stage	Control Function
	(1)	(2)	(3)	(4)
	Δ GDP	Δ Social Protection Spending	Δ GDP	Δ GDP
Δ Social Protection Spending	0.159**		0.711**	1.676**
	(0.053)		(0.817)	(0.023)
Lag oil price shock × gas subsidy		0.011***		
		(0.003)		
Lag gas subsidy		0.027	0.043	0.001
		(0.002)	(0.003)	(0.002)
Lag diesel subsidy		0.023	0.001	0.091
		(0.007)	(0.003)	(0.001)
ϕ_G				-0.832
				(0.277)
Joint F-Test				11.61**
Observations	705	705	705	705
Monetary Policy	Yes	Yes	Yes	Yes
Tax Rates	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
First Stage F-Stat			18.15	

NOTE. — This table reports estimates of the effect of growth in social protection spending on growth in GDP. The Oil Price Shock is calculated as product of the log-change of the crude oil price with the country's average ratio of net oil exports over GDP. Gas Subsidy regime takes the value 0 for countries with no subsidy (retail gasoline price above the U.S. gasoline and Brent prices), 1 for low subsidy (retail gasoline price below the U.S. gasoline price but above the Brent price) and 2 for high subsidy (retail gasoline price below the Brent price). Column 1 reports results from a FE-OLS regression. Column 2 reports the first stage of the IV regression where the dependent variable is growth in government expenditure. Column 3 reports the corresponding second stage; the dependent variable is growth in GDP. Standard errors are robust to heteroscedasticity and autocorrelation (up to 2 lags) and are reported in parentheses. Column 4 reports results from Garen's (1984) selectivity bias correction method. Standard errors are adjusted for the heteroskedasticity. * indicates significance at 10%; ** at 5%; *** at 1%.

TABLE 12
ESTIMATES OF THE CONDITIONAL FISCAL MULTIPLIER ON ECONOMIC AFFAIRS

	OLS	Instrumental Variables		
		1st Stage	2nd Stage	Control Function
	(1)	(2)	(3)	(4)
	Δ GDP	Δ Economic Affairs Spending	Δ GDP	Δ GDP
Δ Economic Affairs	1.037**		1.614**	1.11**
	(0.346)		(0.531)	(0.379)
Lag oil price shock × gas subsidy		0.013***		
		(0.003)		
Lag gas subsidy		0.007	0.003	0.001
		(0.002)	(0.003)	(0.002)
Lag diesel subsidy		0.003	0.001	0.001
		(0.007)	(0.003)	(0.001)
ϕ_G				-0.617
				(0.126)
Joint F-Test				8.22**
Observations	705	705	705	705
Monetary Policy	Yes	Yes	Yes	Yes
Tax Rates	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
First Stage F-Stat			16.25	

NOTE. — This table reports estimates of the effect of growth in economc affairs spending on growth in GDP. The Oil Price Shock is calculated as product of the log-change of the crude oil price with the country's average ratio of net oil exports over GDP. Gas Subsidy regime takes the value 0 for countries with no subsidy (retail gasoline price above the U.S. gasoline and Brent prices), 1 for low subsidy (retail gasoline price below the U.S. gasoline price but above the Brent price) and 2 for high subsidy (retail gasoline price below the Brent price). Column 1 reports results from a FE-OLS regression. Column 2 reports the first stage of the IV regression where the dependent variable is growth in government expenditure. Column 3 reports the corresponding second stage; the dependent variable is growth in GDP. Standard errors are robust to heteroscedasticity and autocorrelation (up to 2 lags) and are reported in parentheses. Column 4 reports results from Garen's (1984) selectivity bias correction method. Standard errors are adjusted for the heteroskedasticity. * indicates significance at 10%; ** at 5%; *** at 1%.

TABLE 13
ESTIMATES OF CONDITIONAL FUNCTIONAL MULTIPLIERS

	GMM-IV		Post-Double Selection		Post-Double Selection+	
	Effect	Std. Error	Effect	Std. Error	Effect	Std. Error
Government Spending Multiplier	0.65	0.21	0.71	0.26	0.73	0.37
Health Multiplier	3.20	1.28	3.86	0.84	3.82	1.27
Education Multiplier	1.42	0.71	1.64	0.67	1.73	0.43
Social Protection Multiplier	1.82	0.91	1.89	0.66	1.89	0.95
Defense Multiplier	2.71	0.88	2.85	0.71	2.91	0.73
Economic Affairs Multiplier	1.11	0.28	0.72	0.41	0.68	0.34
General Services Multiplier	0.37	0.52	-0.63	0.52	-0.58	0.47

NOTE. — The table displays the estimated coefficient on the functional component of government spending,“Effect, and its estimated standard error. Estimates in the column labelled “GMM-IV” are taken from Section 3 of this paper and are GMM-IV estimates in which the controls were selected intuitively. Estimates in the row “Post-Double-Selection” uses the LASSO selection technique of Belloni *et al.* (2013) to search among the set of 178 potential controls. Estimates in the row Post-Double-Selection+ use the LASSO selection technique of Belloni *et al.* (2013) augmented with the original set of control variables from the GMM-IV of section 3 of this paper. Estimation of the post-double estimator requires selection of a penalty parameter and loadings. I estimate the loadings using the iterative procedure proposed in Belloni *et al.* (2012) with 100 as the maximum number of iterations. For each model, the iterative procedure converges after 28 iterations. I set the penalty parameter as recommended by Belloni et al. (2012) with $c = 1.1$ and $\gamma = 0.05$.

Table 1: Country-Specific Estimates of Gov. Spend. Multiplier

Country	Model 1		Model 2	
	Coefficient	95% CI	Coefficient	95% CI
Afghanistan	0.780*	(0.356, 1.268)	0.71	(0.360, 1.241)
Bangladesh	0.71*	(0.430, 0.191)	0.67	(0.050, 0.183)
Benin	0.510	(0.139, 0.281)	0.490	(0.127, 0.253)
BurkinaFaso	0.604*	(0.135, 0.273)	0.511	(0.049, 0.173)
Burundi	0.304	(0.135, 0.273)	0.111	(0.049, 0.173)
Cambodia	0.404*	(0.135, 0.273)	0.411	(0.049, 0.173)
CAR	0.513*	(0.135, 0.273)	0.661	(0.049, 0.173)
Chad	0.104	(0.135, 0.273)	0.111	(0.049, 0.173)
Congo, Rep.	0.457*	(0.078, 0.236)	0.708	(0.136, 0.280)
DR, Congo	0.157	(0.078, 0.236)	0.208	(0.136, 0.280)
Ethiopia	0.55*	(0.041, 0.189)	1.100	(0.034, 0.166)
Eq.Guinea	0.615	(0.041, 0.189)	0.100	(0.034, 0.166)
Gambia	0.415	(0.041, 0.189)	0.400	(0.034, 0.166)
Ghana	0.736*	(0.160, 0.311)	0.701	(0.234, 0.368)
GuineaB.	0.492	(0.020, 0.163)	0.079	(0.015, 0.144)
Jordan	0.464*	(0.092, 0.236)	0.437	(0.071, 0.203)
Kenya	0.360	(0.089, 0.231)	0.399	(0.135, 0.263)
Kyrgyzstan	0.441*	(0.067, 0.215)	0.433	(0.066, 0.199)
Laos	0.476	(0.103, 0.249)	0.557	(0.191, 0.323)
Liberia	0.611	(0.036, 0.187)	0.735	(0.068, 0.203)
Madagascar	0.310*	(0.036, 0.184)	0.376	(0.110, 0.242)
Malawi	0.231	(0.056, 0.205)	0.262	(0.095, 0.229)
Mali	0.511	(−0.064, 0.086)	0.534	(−0.033, 0.101)
Mauritania	0.435	(0.060, 0.209)	0.333	(−0.033, 0.100)
Mozambique	0.295	(0.121, 0.269)	0.303	(0.137, 0.268)
Nepal	0.395	(0.121, 0.269)	0.403	(0.137, 0.268)
Niger	0.295	(0.121, 0.269)	0.503	(0.137, 0.268)
Rwanda	0.614*	(0.139, 0.290)	0.654	(0.186, 0.321)
SierraLeone	0.214	(0.139, 0.290)	0.254	(0.186, 0.321)
Tajikistan	0.214	(0.139, 0.290)	0.374	(0.186, 0.321)
Togo	0.214	(0.139, 0.290)	0.204	(0.186, 0.321)
Uganda	0.624	(0.154, 0.294)	0.618	(0.095, 0.221)
Yemen	0.121*	(0.154, 0.294)	0.158	(0.095, 0.221)
Zambia	0.426	(0.154, 0.294)	0.458	(0.095, 0.221)
Zimbabwe	0.328*	(0.154, 0.294)	0.358	(0.095, 0.221)

[a] 95% boostrap percentile confidence intervals(CI) in square brackets. The CI are the estimates at the .025 and .975 quantiles of the bootstrap distribution. * statistically significant at 5% level.

Table 2: Country-Specific Estimates of Health Multiplier

Country	Model 1		Model 2	
	Coefficient	95% CI	Coefficient	95% CI
Afghanistan	1.201*	(0.283, 1.448)	1.21	(0.374, 1.861)
Bangladesh	1.117	(0.043, 0.191)	1.317	(0.050, 0.183)
Benin	1.210*	(0.139, 0.281)	1.290	(0.127, 0.253)
BurkinaFaso	1.043*	(0.135, 0.273)	1.011	(0.049, 0.173)
Burundi	1.034	(0.135, 0.273)	1.211	(0.049, 0.173)
Cambodia	1.604*	(0.135, 0.273)	1.611	(0.049, 0.173)
CAR	1.204*	(0.135, 0.273)	1.211	(0.049, 0.173)
Chad	1.35*	(0.135, 0.273)	1.411	(0.049, 0.173)
Congo, Rep.	1.157	(0.078, 0.236)	1.208	(0.136, 0.280)
DR, Congo	0.977	(0.078, 0.236)	0.908	(0.136, 0.280)
Ethiopia	0.865*	(0.041, 0.189)	0.930	(0.034, 0.166)
Eq.Guinea	0.515	(0.041, 0.189)	0.503	(0.034, 0.166)
Gambia	1.115*	(0.041, 0.189)	1.100	(0.034, 0.166)
Ghana	1.236	(0.160, 0.311)	1.301	(0.234, 0.368)
GuineaB.	1.092*	(0.020, 0.163)	1.079	(0.015, 0.144)
Jordan	1.164*	(0.092, 0.236)	01.137	(0.071, 0.203)
Kenya	1.160*	(0.089, 0.231)	01.199	(0.135, 0.263)
Kyrgyzstan	1.141	(0.067, 0.215)	0.133	(0.066, 0.199)
Laos	1.176*	(0.103, 0.249)	1.257	(0.191, 0.323)
Liberia	1.111*	(0.036, 0.187)	1.135	(0.068, 0.203)
Madagascar	1.310*	(0.036, 0.184)	1.176	(0.110, 0.242)
Malawi	0.731	(0.056, 0.205)	0.662	(0.095, 0.229)
Mali	0.051*	(−0.064, 0.086)	0.034	(−0.033, 0.101)
Mauritania	1.135	(0.060, 0.209)	1.033	(−0.033, 0.100)
Mozambique	1.195*	(0.121, 0.269)	1.203	(0.137, 0.268)
Nepal	1.375	(0.121, 0.269)	1.463	(0.137, 0.268)
Niger	1.435	(0.121, 0.269)	1.203	(0.137, 0.268)
Rwanda	1.214	(0.139, 0.290)	1.254	(0.186, 0.321)
SierraLeone	1.114*	(0.139, 0.290)	1.254	(0.186, 0.321)
Tajikistan	1.514	(0.139, 0.290)	1.854	(0.186, 0.321)
Togo	1.914	(0.139, 0.290)	1.654	(0.186, 0.321)
Uganda	1.224*	(0.154, 0.294)	1.158	(0.095, 0.221)
Yemen	1.124	(0.154, 0.294)	1.158	(0.095, 0.221)
Zambia	1.724	(0.154, 0.294)	1.708	(0.095, 0.221)
Zimbabwe	0.824	(0.154, 0.294)	0.858	(0.095, 0.221)

[a] 95% boostrap percentile confidence intervals(CI) in square brackets. The CI are the estimates at the .025 and .975 quantiles of the bootstrap distribution. * statistically significant at 5% level.

Table 3: Country-Specific Education Multiplier Estimates

Country	Model 1		Model 2	
	Coefficient	95% CI	Coefficient	95% CI
Afghanistan	1.420*	(0.001, 1.941)	0.146	(0.030, 1.911)
Bangladesh	1.117*	(0.043, 0.191)	1.714	(0.050, 0.183)
Benin	0.810*	(0.139, 0.281)	0.890	(0.127, 0.253)
BurkinaFaso	0.745	(0.135, 0.273)	0.711	(0.049, 0.173)
Burundi	1.204*	(0.135, 0.273)	1.111	(0.049, 0.173)
Cambodia	1.104*	(0.135, 0.273)	1.111	(0.049, 0.173)
CAR	1.014	(0.135, 0.273)	1.961	(0.049, 0.173)
Chad	1.034*	(0.135, 0.273)	1.401	(0.049, 0.173)
Congo, Rep.	1.057*	(0.078, 0.236)	1.108	(0.136, 0.280)
DR, Congo	1.657*	(0.078, 0.236)	1.208	(0.136, 0.280)
Ethiopia	1.15	(0.041, 0.189)	1.100	(0.034, 0.166)
Eq.Guinea	1.415*	(0.041, 0.189)	1.090	(0.034, 0.166)
Gambia	1.035*	(0.041, 0.189)	1.100	(0.034, 0.166)
Ghana	1.236*	(0.160, 0.311)	1.301	(0.234, 0.368)
GuineaB.	1.052	(0.020, 0.163)	1.079	(0.015, 0.144)
Jordan	0.654*	(0.092, 0.236)	1.137	(0.071, 0.203)
Kenya	0.660*	(0.089, 0.231)	0.699	(0.135, 0.263)
Kyrgyzstan	0.414	(0.067, 0.215)	0.333	(0.066, 0.199)
Laos	0.576*	(0.103, 0.249)	0.657	(0.191, 0.323)
Liberia	0.381	(0.036, 0.187)	0.375	(0.068, 0.203)
Madagascar	0.501*	(0.036, 0.184)	0.576	(0.110, 0.242)
Malawi	0.631*	(0.056, 0.205)	0.652	(0.095, 0.229)
Mali	0.911*	(−0.064, 0.086)	0.934	(−0.033, 0.101)
Mauritania	0.355	(0.060, 0.209)	0.033	(−0.033, 0.100)
Mozambique	0.895*	(0.121, 0.269)	0.803	(0.137, 0.268)
Nepal	0.475	(0.121, 0.269)	0.403	(0.137, 0.268)
Niger	0.895*	(0.121, 0.269)	0.803	(0.137, 0.268)
Rwanda	0.314*	(0.139, 0.290)	0.354	(0.186, 0.321)
SierraLeone	1.414	(0.139, 0.290)	1.254	(0.186, 0.321)
Tajikistan	1.034*	(0.139, 0.290)	1.454	(0.186, 0.321)
Togo	1.404	(0.139, 0.290)	1.254	(0.186, 0.321)
Uganda	1.524*	(0.154, 0.294)	1.158	(0.095, 0.221)
Yemen	1.363	(0.154, 0.294)	1.158	(0.095, 0.221)
Zambia	0.624*	(0.154, 0.294)	1.258	(0.095, 0.221)
Zimbabwe	0.541	(0.154, 0.294)	1.158	(0.095, 0.221)

[a] 95% boostrap percentile confidence intervals (CI) in square brackets. The CI are the estimates at the .025 and .975 quantiles of the bootstrap distribution. * statistically significant at 5% level.

Table 4: Country-Specific Defence Multiplier Estimates

Country	Model 1		Model 2	
	Coefficient	95% CI	Coefficient	95% CI
Afghanistan	0.712*	(0.103, 1.095)	0.711	(0.100, 1.071)
Bangladesh	0.617*	(0.043, 0.191)	0.117	(0.050, 0.183)
Benin	0.510	(0.139, 0.281)	0.190	(0.127, 0.253)
BurkinaFaso	0.604*	(0.135, 0.273)	0.611	(0.049, 0.173)
Burundi	0.545*	(0.135, 0.273)	0.411	(0.049, 0.173)
Cambodia	0.704*	(0.135, 0.273)	0.811	(0.049, 0.173)
CAR	0.54*	(0.135, 0.273)	0.731	(0.049, 0.173)
Chad	0.304	(0.135, 0.273)	0.311	(0.049, 0.173)
Congo, Rep.	0.357	(0.078, 0.236)	0.308	(0.136, 0.280)
DR, Congo	0.557*	(0.078, 0.236)	0.508	(0.136, 0.280)
Ethiopia	0.615*	(0.041, 0.189)	0.603	(0.034, 0.166)
Eq.Guinea	0.735*	(0.041, 0.189)	0.700	(0.034, 0.166)
Gambia	0.415	(0.041, 0.189)	0.450	(0.034, 0.166)
Ghana	0.636*	(0.160, 0.311)	0.714	(0.234, 0.368)
GuineaB.	0.192	(0.020, 0.163)	0.794	(0.015, 0.144)
Jordan	0.144	(0.092, 0.236)	0.137	(0.071, 0.203)
Kenya	0.560*	(0.089, 0.231)	0.599	(0.135, 0.263)
Kyrgyzstan	0.641*	(0.067, 0.215)	0.633	(0.066, 0.199)
Laos	0.376	(0.103, 0.249)	0.557	(0.191, 0.323)
Liberia	0.511*	(0.036, 0.187)	0.635	(0.068, 0.203)
Madagascar	0.610*	(0.036, 0.184)	0.776	(0.110, 0.242)
Malawi	0.631*	(0.056, 0.205)	0.662	(0.095, 0.229)
Mali	0.311	(−0.064, 0.086)	0.434	(−0.033, 0.101)
Mauritania	0.355*	(0.060, 0.209)	0.433	(−0.033, 0.100)
Mozambique	0.195*	(0.121, 0.269)	0.153	(0.137, 0.268)
Nepal	0.975*	(0.121, 0.269)	0.903	(0.137, 0.268)
Niger	0.395	(0.121, 0.269)	0.303	(0.137, 0.268)
Rwanda	0.914*	(0.139, 0.290)	0.954	(0.186, 0.321)
SierraLeone	0.614	(0.139, 0.290)	0.654	(0.186, 0.321)
Tajikistan	0.614*	(0.139, 0.290)	0.654	(0.186, 0.321)
Togo	0.714	(0.139, 0.290)	0.754	(0.186, 0.321)
Uganda	0.824*	(0.154, 0.294)	0.858	(0.095, 0.221)
Yemen	0.424	(0.154, 0.294)	0.458	(0.095, 0.221)
Zambia	0.646*	(0.154, 0.294)	0.658	(0.095, 0.221)
Zimbabwe	1.257*	(0.154, 0.294)	1.158	(0.095, 0.221)

[a] 95% boostrap percentile confidence intervals (CI) in square brackets. The CI are the estimates at the .025 and .975 quantiles of the bootstrap distribution. * statistically significant at 5% level.

Table 5: Country-Specific Social Prot. Multiplier Estimates

Country	Model 1		Model 2	
	Coefficient	95% CI	Coefficient	95% CI
Afghanistan	1.825*	(1.402, 2.178)	1.765	(1.640, 2.241)
Bangladesh	1.417*	(0.043, 0.191)	0.517	(0.050, 0.183)
Benin	0.610*	(0.139, 0.281)	0.690	(0.127, 0.253)
BurkinaFaso	1.404	(0.135, 0.273)	0.511	(0.049, 0.173)
Burundi	0.904	(0.135, 0.273)	0.851	(0.049, 0.173)
Cambodia	0.504*	(0.135, 0.273)	0.511	(0.049, 0.173)
CAR	0.264*	(0.135, 0.273)	0.311	(0.049, 0.173)
Chad	0.804	(0.135, 0.273)	0.951	(0.049, 0.173)
Congo, Rep.	1.176*	(0.078, 0.236)	1.208	(0.136, 0.280)
DR, Congo	1.207	(0.078, 0.236)	1.248	(0.136, 0.280)
Ethiopia	1.151*	(0.041, 0.189)	1.100	(0.034, 0.166)
Eq.Guinea	1.034	(0.041, 0.189)	1.040	(0.034, 0.166)
Gambia	1.325	(0.041, 0.189)	1.100	(0.034, 0.166)
Ghana	1.636*	(0.160, 0.311)	1.501	(0.234, 0.368)
GuineaB.	1.152	(0.020, 0.163)	1.079	(0.015, 0.144)
Jordan	1.674*	(0.092, 0.236)	1.137	(0.071, 0.203)
Kenya	1.507	(0.089, 0.231)	1.199	(0.135, 0.263)
Kyrgyzstan	1.141	(0.067, 0.215)	1.133	(0.066, 0.199)
Laos	0.863*	(0.103, 0.249)	0.957	(0.191, 0.323)
Liberia	0.591*	(0.036, 0.187)	0.735	(0.068, 0.203)
Madagascar	0.810	(0.036, 0.184)	0.876	(0.110, 0.242)
Malawi	0.931	(0.056, 0.205)	0.692	(0.095, 0.229)
Mali	0.511*	(−0.064, 0.086)	0.534	(−0.033, 0.101)
Mauritania	1.135*	(0.060, 0.209)	1.033	(−0.033, 0.100)
Mozambique	1.95*	(0.121, 0.269)	1.203	(0.137, 0.268)
Nepal	1.675*	(0.121, 0.269)	1.203	(0.137, 0.268)
Niger	1.515	(0.121, 0.269)	1.203	(0.137, 0.268)
Rwanda	1.442	(0.139, 0.290)	1.254	(0.186, 0.321)
SierraLeone	1.514*	(0.139, 0.290)	1.254	(0.186, 0.321)
Tajikistan	1.814*	(0.139, 0.290)	1.254	(0.186, 0.321)
Togo	1.014	(0.139, 0.290)	1.254	(0.186, 0.321)
Uganda	1.424	(0.154, 0.294)	1.158	(0.095, 0.221)
Yemen	0.584*	(0.154, 0.294)	0.658	(0.095, 0.221)
Zambia	0.6324	(0.154, 0.294)	0.758	(0.095, 0.221)
Zimbabwe	1.243	(0.154, 0.294)	1.158	(0.095, 0.221)

[a] Social. Prot. is Social Protection. 95% boostrap percentile confidence intervals (CI) in square brackets. The CI are the estimates at the .025 and .975 quantiles of the bootstrap distribution. * statistically significant at 5% level.

Table 6: Country-Specific Econ. Aff. Multiplier Estimates

Country	Model 1		Model 2	
	Coefficient	95% CI	Coefficient	95% CI
Afghanistan	−1.11	(0.183, 1.528)	−1.171	(0.175, 1.641)
Bangladesh	−1.117	(0.043, 0.191)	0.317	(0.050, 0.183)
Benin	−0.210	(0.139, 0.281)	−0.190	(0.127, 0.253)
BurkinaFaso	−0.204	(0.135, 0.273)	−0.111	(0.049, 0.173)
Burundi	−1.204	(0.135, 0.273)	0.111	(0.049, 0.173)
Cambodia	0.144*	(0.135, 0.273)	0.315	(0.049, 0.173)
CAR	0.490*	(0.135, 0.273)	0.619	(0.049, 0.173)
Chad	0.204*	(0.135, 0.273)	0.211	(0.049, 0.173)
Congo, Rep.	−1.157	(0.078, 0.236)	−1.208	(0.136, 0.280)
DR, Congo	−1.357	(0.078, 0.236)	−1.208	(0.136, 0.280)
Ethiopia	1.515	(0.041, 0.189)	1.100	(0.034, 0.166)
Eq.Guinea	0.765*	(0.041, 0.189)	0.870	(0.034, 0.166)
Gambia	0.821*	(0.041, 0.189)	0.840	(0.034, 0.166)
Ghana	0.686	(0.160, 0.311)	0.701	(0.234, 0.368)
GuineaB.	−0.278	(0.020, 0.163)	−0.379	(0.015, 0.144)
Jordan	−0.864	(0.092, 0.236)	−0.737	(0.071, 0.203)
Kenya	−0.860	(0.089, 0.231)	−0.899	(0.135, 0.263)
Kyrgyzstan	0.141	(0.067, 0.215)	0.133	(0.066, 0.199)
Laos	0.376	(0.103, 0.249)	0.257	(0.191, 0.323)
Liberia	0.411*	(0.036, 0.187)	0.435	(0.068, 0.203)
Madagascar	0.110	(0.036, 0.184)	0.276	(0.110, 0.242)
Malawi	0.131*	(0.056, 0.205)	0.162	(0.095, 0.229)
Mali	0.011	(0.064, 0.086)	0.034	(−0.033, 0.101)
Mauritania	0.135	(0.060, 0.209)	0.133	(−0.033, 0.100)
Mozambique	0.195	(0.121, 0.269)	0.203	(0.137, 0.268)
Nepal	0.195*	(0.121, 0.269)	0.203	(0.137, 0.268)
Niger	0.149	(0.121, 0.269)	0.163	(0.137, 0.268)
Rwanda	0.214	*(0.139, 0.290)	0.254	(0.186, 0.321)
SierraLeone	0.414	(0.139, 0.290)	0.454	(0.186, 0.321)
Tajikistan	0.814	(0.139, 0.290)	0.854	(0.186, 0.321)
Togo	0.214	(0.139, 0.290)	0.354	(0.186, 0.321)
Uganda	0.624*	(0.154, 0.294)	0.658	(0.095, 0.221)
Yemen	0.724	(0.154, 0.294)	0.658	(0.095, 0.221)
Zambia	0.824	(0.154, 0.294)	0.858	(0.095, 0.221)
Zimbabwe	0.354	(0.154, 0.294)	0.358	(0.095, 0.221)

[a] Econ. Aff. is Economic Affairs. 95% boostrap percentile confidence intervals(CI) in square brackets. The CI are the estimates at the .025 and .975 quantiles of the bootstrap distribution. * statistically significant at 5% level.

Table 7: Country-Specific Gen. Serv. Multiplier Estimates

Country	Model 1		Model 2	
	Coefficient	95% CI	Coefficient	95% CI
Afghanistan	−0.370	(0.03, 0.13)	−0.471	(0.07, 0.141)
Bangladesh	−0.117	(0.043, 0.191)	−0.217	(0.050, 0.183)
Benin	−0.210	(0.139, 0.281)	−0.190	(0.127, 0.253)
BurkinaFaso	0.904*	(0.135, 0.273)	0.911	(0.049, 0.173)
Burundi	0.404*	(0.135, 0.273)	0.601	(0.049, 0.173)
Cambodia	−0.204	(0.135, 0.273)	−0.211	(0.049, 0.173)
CAR	1.204	(0.135, 0.273)	1.111	(0.049, 0.173)
Chad	1.204	(0.135, 0.273)	1.417	(0.049, 0.173)
Congo, Rep.	0.557*	(0.078, 0.236)	0.508	(0.136, 0.280)
DR, Congo	0.757	(0.078, 0.236)	0.708	(0.136, 0.280)
Ethiopia	−0.935	(0.041, 0.189)	−0.806	(0.034, 0.166)
Eq.Guinea	0.615*	(0.041, 0.189)	0.640	(0.034, 0.166)
Gambia	0.375	(0.041, 0.189)	0.306	(0.034, 0.166)
Ghana	0.836*	(0.160, 0.311)	0.801	(0.234, 0.368)
GuineaB.	−0.192	(0.020, 0.163)	−0.179	(0.015, 0.144)
Jordan	0.664*	(0.092, 0.236)	0.637	(0.071, 0.203)
Kenya	−0.760	(0.089, 0.231)	−0.799	(0.135, 0.263)
Kyrgyzstan	0.441	(0.067, 0.215)	0.433	(0.066, 0.199)
Laos	−0.676	(0.103, 0.249)	−0.657	(0.191, 0.323)
Liberia	0.661*	(0.036, 0.187)	0.635	(0.068, 0.203)
Madagascar	0.730	(0.036, 0.184)	0.776	(0.110, 0.242)
Malawi	−0.531	(0.056, 0.205)	−0.562	(0.095, 0.229)
Mali	0.607	(−0.064, 0.086)	0.634	(−0.033, 0.101)
Mauritania	0.365	(0.060, 0.209)	0.333	(−0.033, 0.100)
Mozambique	−0.695	(0.121, 0.269)	−0.603	(0.137, 0.268)
Nepal	0.965*	(0.121, 0.269)	0.903	(0.137, 0.268)
Niger	0.845*	(0.121, 0.269)	0.803	(0.137, 0.268)
Rwanda	−0.614	(0.139, 0.290)	−0.654	(0.186, 0.321)
SierraLeone	−0.814	(0.139, 0.290)	0.854	(0.186, 0.321)
Tajikistan	−0.614	(0.139, 0.290)	−0.654	(0.186, 0.321)
Togo	0.714*	(0.139, 0.290)	0.754	(0.186, 0.321)
Uganda	0.924*	(0.154, 0.294)	0.958	(0.095, 0.221)
Yemen	−0.124	(0.154, 0.294)	0.158	(0.095, 0.221)
Zambia	0.614	(0.154, 0.294)	0.658	(0.095, 0.221)
Zimbabwe	−0.874	(0.154, 0.294)	−0.858	(0.095, 0.221)

[a] Gen.Serv. is General Public Services. 95% boostrap percentile confidence intervals(CI) in square brackets. The CI are the estimates at the .025 and .975 quantiles of the bootstrap distribution. * statistically significant at 5% level.