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Crowding-Out or Crowding-In? Public and Private Investment in India

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Crowding-Out or Crowding-In? Public and Private Investment in India [1]

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Abstract

This paper contributes to the debate on the relationship between public-capital accumulation and private investment in India along the following dimensions. First, acknowledging major structural changes that the Indian economy has undergone in the past three decades, we study whether public investment in recent years has become more or less complementary to private investment in comparison to the period before 1980. Second, we construct a novel data-set of quarterly aggregate public and private investment in India over the period 1996Q2-2015Q1 using investment-project data from the CapEx-CMIE database. Third, embedding a theory-driven long-run relationship on the model, we estimate a range of Structural Vector Error Correction Models (SVECMs) to re-examine the public and private investment relationship in India. Identification is achieved by decomposing shocks into those with transitory and permanent effects. Our results suggest that while public-capital accumulation crowds out private investment in India over 1950-2012, the opposite is true when we restrict the sample post 1980 or conduct a quarterly analysis since 1996Q2. This change can most likely be attributed to the policy reforms which started during early 1980s and gained momentum after the 1991 crises.

JEL Classification Numbers: C30; C32; E22; H54.

Keywords: India; Public investment; Private investment; Crowding in; Crowding out; Permanent shocks; Structural identification; Vector error correction models.

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I. INTRODUCTION

The relationship between public-capital accumulation and private investment has received renewed interest among academics and policy makers alike in the aftermath of the global financial crisis. On the one hand, higher public investment may "crowd out" private expenditure on capital goods, irrespective of the financing mechanism (including through levying taxes or issuing debt). On the other hand, higher government spending on infrastructure facilities (like roads, highways, and power) and/or health and education may have a complementary impact on private sector investment by raising the marginal productivity of private capital. The literature, which mostly relies on time-series and cross-country regression analysis, finds mixed predictions on the relationship between private investment and public-capital accumulation. We re-examine this relationship in India by estimating a Structural Vector Error Correction Model (SVECM) in three variables (public investment, private investment, and output) over the period 1950-2012.

We also investigate whether this relationship has changed over time after the policy reforms that started during 1980s (using annual observations) as well as post liberalization in early 1990s (using quarterly data over the period 1996Q2-2015Q1 from the CapEx-CMIE database), and compute the corresponding rupee response of private investment to an equivalent increase in public investment. Our main contribution to the literature, on public-private investment relation in emerging market economies, is our novel identification strategy and the use of theory-driven long-run relationships in the analysis. While we solve the identification problem by imposing restrictions on the long-run impact of the shocks, we motivate those restrictions from an economic theory perspective, namely, the "great ratio" of investment to output. We estimate a SVECM and decompose the structural shocks into those with permanent and transitory effects on the level of the variables for identification. We find that while public-capital accumulation crowds out private investment in India over the full sample 1950-2012, the opposite is true when we restrict the sample post 1980 or employ a quarterly model of public-private investment since 1996Q2, largely due to policy reforms introduced since the early 1990s.

We rely on long-run restrictions for identification, as they are typically free of particular model assumptions and are motivated from what is generally agreed-upon in empirical macroeconomic modeling, see Chudik et al. (2015a, 2015b) for details. This is in contrast to solving the identification problem in VAR models by imposing short-run restrictions, which requires a well-defined economic theory of the short-run and is more restrictive (especially in annual data).[1] Specifically, we impose a long-run relationship between the three variables

[1] For example, most economists agree that monetary policy shocks are neutral in the long run, whereas productivity shocks can have permanent effects. This idea was first introduced in the context of a bivariate model in Blanchard and Quah (1989).

considered based on the "great ratio" of aggregate investment to output. Regarding identification, we assume that private-sector demand disturbances have transitory effects (given evidence for the presence of one cointegrating, or long run, relationship among the three variables considered), while the two structural innovations that have permanent effects are productivity shocks and (possibly) public investment innovations. As evidence, Binder and Pesaran (1999) argue that in the long run, the evolution of per-capita output is largely determined by technological process. Furthermore, endogenous growth models predict that per-capita output follows a stochastic trend where certain policy changes (i.e. productive public-investment decisions) may have long-run consequences for the level of output, see Jones (1995) and Kocherlakota and Yi (1996).[2]

Although there is a large body of literature analyzing the relationship between public-capital accumulation and private investment, the empirical findings are mixed and research on developing and emerging market economies is rather limited. What is even more scarce is an attempt to identify whether the interaction between public and private investment has changed over time in those developing and emerging market economies which have witnessed significant structural reforms like deregulation of domestic/foreign goods markets (liberalization). Aschauer (1989a, 1989b) argues that public investment in the United States, especially on infrastructure facilities, has a significant positive impact on private investment by increasing productivity. While this conclusion of complementarity between public and private investment was further supported by Greene and Villanueva (1991) and Blejer and Khan (1984), there were also some strong criticism of Aschauer's results by Evans and Karras (1994) among others.

Erden and Holcombe (2005) compare the interaction of public and private investment in developing and developed economies, and conclude that while public investment is complementary to private investment in developing countries, the effect is opposite in developed countries. The difference in these results is attributed to structural differences between the two types of economies: while public investment may provide the necessary infrastructure facilities in developing countries and hence boost private investment, in developed economies the public sector is already large and may compete with the private sector. For the case of India, Mitra (2006) estimates a structural VAR model (using data over 1969–2005) in three variables (public investment, private investment, and output), and argues that public investment "crowds out" private investment. Serven (1999) analyzes how public and private investment interact with each other in India, and reports evidence of crowding out in the short run and crowding in of private capital due to infrastructure investment in the long run.

[2] Rodrik and Subramanian (2005) identify a productivity-boosting role for public infrastructure investment in India. Serven (1999) finds that government investment in infrastructure projects in India "crowds in" private investment over the long run.

Our main departure from these studies is the use of theory-driven long-run restrictions in our structural vector error correction models.[3] Garratt et al. (2012) argues that there are inherent difficulties with the interpretation that are given to the impulse responses that are obtained under the Structural VAR approach, and stresses the importance of embedding structural long-run relationships in unrestricted VAR models as their steady-state solutions.[4] To the best of our knowledge, no previous study has employed this method to study the relationship between private and public investment in India.

The findings of our paper are in general agreement with Mitra (2006) and Serven (1999) when, like these earlier studies, our data encompasses annual observations before 1980. However, we find that unlike in the period 1950-2012, public-capital accumulation is complementary to private-sector investment after 1980. Our "crowding in" finding is corroborated by similar results obtained from a SVECM on quarterly data over 1996Q2-2015Q1, using public and private investment data constructed from the Indian CapEx-CMIE database.

The remainder of the paper is organized as follows. Section 2 discusses the econometric methodology and outlines our identification approach. Section 3 describes the data while section 4 presents the empirical findings. Finally, Section 5 concludes and offers some policy recommendations.

II. Structural VECM

We estimate a range of SVECMs with the baseline specifications including log per capita output, y_t, public investment, gi_t, and private investment, pi_t. As Appendix B discusses, all the variables are integrated of order one with evidence of one cointegrating relation among the three variables. The long run relationship between y_t, gi_t and pi_t can be motivated from the stationarity of the "great ratio" of aggregate investment and output. Appendix A expresses this relationship as $\beta_1 gi_t + \beta_2 pi_t - y_t$ where both β_1 and β_2 are less than 1. We embed this relationship in the following reduced form vector error correction model:

$$\Delta \mathbf{z}_t = \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{z}_{t-1} + \sum_{i=1}^{m} \Gamma_i \Delta \mathbf{z}_{t-i} + \mathbf{u}_t \tag{1}$$

where $\mathbf{z}_t = (y_t, gi_t, pi_t)'$ is a (3×1) vector of endogenous variables, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are (3×1)

[3] Serven (1999) does find cointegration, but estimates a single equation conditional model.

[4] Mitchell (2000) shows that ignoring cointegration when it indeed exists—by estimating a VAR in first differences—can result in misspecification error and bias at both long and short run horizons in the impulse responses.

vectors of loading coefficients and cointegrating vectors respectively, Γ_i is a (3×3) parameter matrix.[5] Finally, $\mathbf{u}_t$ represent the reduced form residuals $(u_t^y, u_t^{gi}, u_t^{pi})$.

To express the reduced form residuals in terms of structural shocks, $\mathbf{u}_t$ can be represented as $\mathbf{B}\boldsymbol{\varepsilon}_t$, where $\mathbf{B}$ is a (3×3) matrix, while $\boldsymbol{\varepsilon}_t$ represent the structural innovations $(\varepsilon_t^y, \varepsilon_t^{gi}, \varepsilon_t^{pi})$ of the system. Specifically, ε_y denotes a productivity shock, ε_t^{gi} a structural disturbance to public investment, and ε_t^{pi} can be motivated as a demand shock. Identification is usually achieved by imposing short run restrictions on the matrix $\mathbf{B}$—See for e.g., Blanchard and Perotti (2002) for details.[6] This requires a well-defined economic theory of the short-run dynamics and can be rather restrictive in data with annual frequency. Our identification strategy, instead, relies on long-run restrictions as they are typically free of particular model assumptions and are motivated from what is generally agreed-upon in empirical macroeconomic modelling.[7] We take the structural innovations in productivity or (potentially) public investment to have long term effects on the variables and demand shock, ε_{pi}, to have transitory effects. Our choice of public investment having a long term impact on output is motivated from the endogenous growth literature which highlights that certain policy changes (like productive public-investment decisions) may have long run consequences on the level of output, see Cashin (1995), Jones (1995) and Kocherlakota and Yi (1996). Furthermore, Aschauer (1989b) reports public investment in 'core' infrastructure projects like in transport, communication, water systems, etc. to have significant impact on productivity (and hence output) in the long-run.

The long-term relationship between y_t, gi_t, and pi_t also implies one transitory and two permanent shocks. We follow Breitung et al. (2004) in identifying the two permanent shocks.[8] Specifically, from Granger's Representation Theorem the process in equation (1) can be represented in the following Beveridge-Nelson moving average representation

$$\Delta \mathbf{z}_t = \underbrace{\boldsymbol{\Xi} \sum_{i=1}^{t} \mathbf{u}_i}_{\text{I(1)}} + \underbrace{\sum_{j=0}^{\infty} \boldsymbol{\Xi}_j^* \mathbf{u}_{t-j}}_{\text{I(0)}} + \mathbf{z}_0^* \tag{2}$$

[5] Given the ordering of the variables, $\boldsymbol{\beta}$ can be equivalently written as $(1, -\beta_1, -\beta_2)$.

[6] See Kilian (2013) for relevant literature on identification using short-run (recursive and non-recursive) and long run restrictions.

[7] The idea of imposing restrictions on the long-run response of variables to shocks was first motivated by Blanchard and Quah (1989) in a bivariate model of log GNP and unemployment rate. They argue that unlike demand disturbances, supply shocks have a long run impact on output; see also King et al. (1991) and Gali (1999).

[8] For a discussion on SVECMs see e.g., King et al. (1991), Gonzalo and Ng (2001), and Pagan and Pesaran (2008).

where $\mathbf{z}_0^*$ contains the initial values, while Ξ_j^* are absolutely summable where the matrices Ξ_j^* converge to zero as $j \to \infty$. The $\Xi \sum_{i=1}^{t} \mathbf{u}_i$ is the common trends term which represents the long run effect of the shocks. In a K variable system with r cointegrating vectors, the matrix

$$\Xi = \boldsymbol{\beta}_\perp \left[\boldsymbol{\alpha}_\perp' \left(I_K - \sum_{i=1}^{m} \Gamma_i \right) \boldsymbol{\beta}_\perp \right]^{-1} \boldsymbol{\alpha}_\perp' \tag{3}$$

has reduced rank $K - r$. Given the presence of $K - r$ common trends, at most r of the underlying structural innovations can have transitory effects on the variables of the system. This is because the matrix Ξ can have at most $K - r$ columns of zeros. Correspondingly, the remaining $K - r$ structural innovations have permanent effects. In our case of three variables and one cointegrating vector, the matrix Ξ is of rank 2, with one transitory and two permanent shocks with at most one column of zeros. This distinction between transitory and permanent shocks enables more maneuverability to identify the SVECM through long-run restrictions, in addition to allowing specification of short run restrictions in the contemporaneous matrix $\mathbf{B}$ (if required).

The long run effects of the structural innovations are obtained by substituting $\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t$ in the common trends term of equation (2) to give $\Xi\mathbf{B} \sum_{i=1}^{t} \boldsymbol{\varepsilon}_i$. Hence the matrix $\Xi\mathbf{B}$ captures the long run effects of the structural innovations. Since matrix $\mathbf{B}$ is nonsingular, the long run matrix $\Xi\mathbf{B}$ is also of rank 2 with at most one column of zeros. Therefore, the presence of one cointegrating vector imposes two independent restrictions.[9] Since identification of r transitory shocks requires $r(r-1)/2$ restrictions, the transitory shock, ε_t^{pi}, is already identified in our model. Finally, the $(K-r)(K-r-1)/2 = 1$ restriction is required to identify the $K - r = 2$ permanent shocks in our model.[10] Together, $r(K-r) + r(r-1)/2 + (K-r)(K-r-1)/2 = 3$ gives the total required $K(K-1)/2$ restrictions for local just-identification of the structural innovations. We distinguish the two permanent shocks by restricting the structural disturbance associated with government investment to have no long-run impact on private investment. Hence, our short and long run matrices are:

$$\mathbf{B} = \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix}, \mathbf{B}\Xi = \begin{bmatrix} * & * & 0 \\ * & * & 0 \\ * & 0 & 0 \end{bmatrix} \tag{4}$$

[9] The reduced rank of $K - r$ for the matrix $\Xi\mathbf{B}$ implies that r zero columns impose $r(K-r)$ independent restrictions and not rK restrictions.

[10] This restriction can be placed either in the contemporaneous matrix $\mathbf{B}$ or in the long run matrix $\Xi\mathbf{B}$ with at least $r(r-1)/2 = 0$ restrictions imposed on the contemporaneous matrix $\mathbf{B}$.

III. Data

Our baseline specification involves annual Indian data on GDP, public and private sector gross fixed capital formation for the period 1950-2012.[11] The data is from National Account Statistics as published by the Indian Central Statistical Office. All the variables are measured in real per capita terms (in 2004-05 prices).

The quarterly frequency data is from the CapEx database of the Centre for Monitoring of Indian Economy (CMIE), which has been monitoring India's investment activity since its creation in 1976. The CapEx database provides systematic coverage of investment projects that entail a capital expenditure of 10 million rupees or more, beginning in 1996 and comprising about 45,000 projects. As there is no one source for investment-projects information, the CapEx data is compiled from all available credible sources. However, this data should not be seen as comprehensive or perfect in its coverage.

We aggregate project-level costs into quarterly time-series for sector- and industry-level investment activity. Given the lack of data on actual quarterly spending profiles, we estimate the quarterly investment activity on the basis of project-level information on total costs and various project events, such as dates of announcement, implementation, obtainment of regulatory clearances, completion, abandonment, etc. For projects that have been completed, the total project cost is apportioned into cash flow on the basis of the length of time between beginning of a project and its completion. For current investment and abandoned or shelved projects, the expected duration is based on the average length of comparable investment undertakings with regard to economic sector and industry (those that have been completed). In addition, we time-allocate cash flow across periods on the basis of equal discounted cash flow using the economy-wide investment cost trends (using gross fixed capital formation deflators). Nonetheless, using this methodology we are not able to account for cost overruns or savings.

For each sector and industry, we construct two measures of investment spending that differ with respect to treatment of abandoned and shelved investments. The first measure includes estimated investment spending on such projects up to the point that investment was declared abandoned or shelved. The second measure assigns zero spending to such projects. The latter measure thus narrows investment activity only to projects that are more likely to directly make up a productive capital stock capacity. Given that we are not able to isolate current investments that may eventually become abandoned or shelved, robustness checks with a trimmed end-point were conducted.[12]

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[11] All variables are national aggregates.

[12] The correlation between the new series (on an annual basis) with public and private gross fixed capital formation from National Accounts Statistics is 0.95 over the period 1995-2012.

IV. EMPIRICAL FINDINGS

This section discusses the results of models with annual frequency as well of those with quarterly investment data. Our baseline specification (hereafter Model 1) contains annual data on y_t, gi_t, and pi_t over the period 1950-2012 (63 observations). We treat this specification as the baseline to enable comparison with earlier studies like Mitra (2006) and Serven (1999), which also used annual data on roughly comparable (though shorter) samples. We also check whether private investment responds differently to accumulation of public infrastructure capital like electricity, railways, other transport, and communication, while keeping the sample period and identification strategy unchanged. Accounting for this heterogeneity is important as public infrastructure projects can raise the profitability of private production and thereby encourage private investment. To test this hypothesis, we estimate Model 2 with variables y_t, gi_t^{infr}, and pi_t, where gi_t^{infr} denotes investment in infrastructure sectors.[13]

Columns 1 and 2 of Table 3 report the estimated loading coefficients and cointegrating vectors respectively. The $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ vectors of Models 1 and 2 are reported in rows 1 and 2, respectively.[14] Although a discussion of causality cannot be made on the basis of cointegrating vectors alone, it is reassuring to observe that the estimated coefficients on public and private investment have the theoretically-correct sign in both models. The estimated long run relationships in both models underline a positive relation between output, public and private investment. Next we identify Models 1 and 2 based on these long run restrictions as discussed in section 2. The zeros in the $\mathbf{B\Xi}$ matrix are the long run identification restrictions.

The estimated short $(\mathbf{B})$ and long run $(\mathbf{B\Xi})$ matrices of Models 1 and 2 are reported in rows 1 and 2 of table 4, respectively. Given the ordering of the variables, $(y, gi, pi)'$ and $(y, gi^i, pi)'$ respectively, we observe that a structural innovation in public investment crowds out private investment in the short run in both models. The effect on output due to ε_t^{gi} on the other hand is positive and statistically significant in both models on impact as well as in the long run.[15] Figure 1, columns 1 and 2, shows the corresponding impulse responses of variables to one standard deviation shocks in productivity and public investment.

For Model 1, as can be seen from the Panel (a) of Figure 1, the impact of a productivity shock on public investment is not significantly different from zero over both the short-term and the long run, while the response of private investment to a productivity shock is significantly positive, both on impact and over the long run. Panel (b) shows the response of output and private investment to a structural innovation in public investment. As the graphs show, the

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[13]The industry-wise investment data does not disaggregate data into public and private sector. Therefore we focus on the industries where most of the investment in the sample period came from the public sector.

[14]The coefficients corresponding to output in the cointegrating vectors are normalized to one.

[15]Note that the long run impact of private investment to ε_{gi} is already restricted to zero.

response of output is positive throughout, while private investment is shown to be temporarily crowded out by public investment. This response is statistically significant for the first 3 years after the shock; thereafter the long run response converges to zero.

The impulse responses of Model 2, reported in column 2 of Figure 1, are very similar to those of Model 1. Here gi_t^{infr} does not respond significantly to a productivity shock, while private investment's response is positive and significantly different from zero (after 1 year), and grows over time. The response of output is also very comparable to that reported in column 1. Most importantly, the crowding out result for private investment in response to a shock in public infrastructure investment stands as compared to Model 1.

Overall, the results of Models 1 and 2 suggest that over the whole sample, 1950-2012, public capital accumulation crowds out private investment in the short run. Furthermore, we do not find any significant differences if we focus our attention only on public investment in infrastructure. This may be because large investment efforts of the public sector over the last three decades were concentrated on infrastructure capital in areas such as agricultural irrigation, transport, telecommunications and power, so the results of Model 2 are very similar to those of Model 1 with aggregate public investment.

These findings are not surprising, as India relied on a state-led, inward-oriented growth strategy for more than three decades post independence. A key component of this strategy was rapid industrialization based on capital-intensive industries, guided by the central plans of government, see Serven (1999) for details. The comprehensive licensing of firms' entry, expansion and diversification plans; reservation of entire productive sectors for the state; high barriers to foreign trade and investment protecting domestic production from external competition; and mandatory credit allocation schemes imposed on the banking system were key components of this strategy, as noted by Serven (1999).

To understand the magnitude of crowding out in our baseline specification, we compute interim multipliers after one, two, and three years for private sector investment in response to a one rupee increase in public investment.[16] A one rupee increase in public investment is shown to crowd out private investment by 0.60, 0.31, and 0.17 rupees after one, two, and three years, respectively. Overall, our baseline results of crowding out in the short run are close to those obtained in past studies by Mitra (2006) and Serven (1999); both of whom report similar short run dynamics.

Although the analysis in Models 1 and 2 is useful to compare with similar earlier studies, it does not acknowledge the substantial structural changes that the Indian economy has undergone during the past three decades. Starting from late 1970s and throughout the 1980s,

[16]To calculate the multipliers, we first compute the elasticities of private investment to public investment ε_{gi}^{pi} over the three years, and divide them by the average ratio of government to private investment over the whole sample.

the Indian economy witnessed reforms in industrial and trade policies. These included deregulation of the domestic market which implied loosening of restrictions on entry, expansion and output mix. Trade reforms were aimed at reducing quantitative controls on import goods, resulting in availability of high quality machinery and capital goods.

Furthermore, the 1991 liberalization process marked a complete restructuring of major policy areas, see Ahluwalia (2002) among others. License restrictions were abolished and all except a few industries were made open to the private sector. Import quotas were eliminated and there was a substantial reduction in tariff rates. Monetary policy focused on price stability and availability of credit to investors. There was a substantial easing of restrictions on the banking sector including a reduction of the cash reserve ratio (CRR) and the statutory liquidity ratio (SLR). Correspondingly, empirical studies on India generally highlight two key structural breaks in the growth rate of GDP. While Rodrik and Subramanian (2005) and DeLong (2003) report a break in 1980s, Ahluwalia (2002) (among others) attribute the break to 1990s due to the economic reforms following the 1991 balance of payments crisis.

We examine whether the response of private investment to public capital accumulation has changed in the latter half of our sample. We first check for the existence of a break during the period 1975-2000 in our sample, using Chow break-point and Chow-forecast tests.[17] Instead of choosing a single break date, we perform the test assuming the break-point to be anytime between 1975-2000 and repeat the test for each year in the sample. For both tests, the null is of parameter constancy and high test statistics result in the rejection of the null. We use 2000 bootstrapped replications to compute the p-values for the tests. The results indicate that the null of parameter constancy is rejected for a range of years during 1975-2000, which provides evidence towards a true underlying break in the model. We select 1980 as the year of the break as it corresponds to the year that gives the highest values of the break-point and split-sample test statistics. Without rejecting the possibility of a second break in early 1990s, we find strong evidence of a break around 1980, in agreement with the findings of Rodrik and Subramanian (2005) among others.[18]

With evidence of a break point in 1980, we re-estimate Model 3 in y_t, gi_t, and pi_t over 1980-2012. The estimated loading and cointegrating vectors are reported in row 3 of Table 3, while the short and long run matrices are reported in row 3 of Table 4. The impulse responses are shown in Figure 1, column 3. The graphs show that the response of public and private investment to productivity shocks, and the output response to a public investment shock, are very similar to Model 1 (column 1). However, the response of private investment to public capital accumulation differs significantly from earlier specifications. In this specification, a policy-induced increase in public investment significantly *crowds in* private investment in the

[17]They test the stability of the parameters of model as a whole.

[18]Our analysis of unit root test with two structural breaks as discussed in Clemente et al. (1998) shows breaks in 1983-1984 for y, gi, and pi. A second break is also indicated for y and pi at 1996.

short run. The calculated interim multipliers are 0.37, 0.16, and 0.07 after the first, second, and third years, respectively. This exercise, therefore, indicates that public capital accumulation may have become more complementary to private investment since the early 1980s.

A. Quarterly analysis using post-liberalization data

While Rodrik and Subramanian (2005) argue that the pickup in India's economic growth preceded the 1991 liberalization by a full decade, there is a consensus in the literature on the role of pro-market reforms of 1990s in transforming the Indian economy. Spurred by a balance of payments crisis in 1991, Indian policy-makers began liberalizing the economy by slashing trade barriers, attracting foreign investment, dismantling the license raj regime, and beginning privatization. The economy started to boom afterwards and graduated from the so-called "Hindu rate of growth". This section investigates whether the relationship between public and private investment has changed after these policy reforms.

We again use the CapEx-CMIE database to construct the quarterly series of public and private investment in India. As we discussed in the data section, we construct two alternative measures of investment: *type 1* which counts investment projects even for failed ones ($i.e.$ where investment is counted until the project is either completed, shelved, or abandoned); and *type 2* which simply does not consider failed projects in the construction of the two investment series. Model 4 corresponds to the case where the investment series are constructed as type 1, gi_t^1 and pi_t^1 for public and private sectors, respectively. Model 5 considers investment series calculated as type 2. We treat Model 5 as our preferred specification because type 2 series abstract from making any assumptions on the investment-flow from projects that possibly never started. Finally, analogous to the exercise in annual data, Model 6 replaces gi_t^2 with $gi_t^{2,\text{infra}}$ where $gi_t^{2,\text{infra}}$ is the public investment series on infrastructure sectors.

Rows 4, 5, and 6 of Table 3 report the loading coefficients and cointegrating vectors corresponding to Models 4, 5, and 6, respectively. The signs of estimated coefficients on public and private investment in the long run relationships are broadly as expected but smaller in magnitude than those obtained in annual data estimations.[19] The estimated short and long run matrices $\mathbf{B}$ and $\mathbf{B\Xi}$ for the three models are reported in rows 4, 5, and 6 of Table 4. The corresponding impulse responses are shown in columns 1, 2 and 3 of Figure 2. As row 1 of Figure 2 shows, for all the 3 specifications, the response of public investment to a productivity shock is positive and statistically significant after 4-6 quarters. Similar to the impulse responses in annual data, the response of private investment (row 2) to a productivity shock is

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[19]The relatively smaller size of the coefficients in comparison to the annual results may be due to the higher frequency of data in Models 4-6. Also, the investment series constructed using investment-project announcements are only proxies for the actual investment activities.

also positive and statistically significant in all the models. The response of output to a policy-induced change in public investment (panel b) is not significantly different from zero in the first 8 quarters in Model 4. However, there is a statistically significant positive impact on output from a public investment shock over the first 8 quarters in Models 5 and 6 (which continue to be small and positive in the long run).

Finally, the impulse responses of private investment to a structural innovation in government investment are reported in the last row of Figure 2. Reassuringly and in agreement with the earlier results from Model 3, none of the three quarterly specifications predict crowding out of private investment. On the contrary, under our preferred specification, Model 5, there is evidence for a positive and significant *crowding in* of private investment by public sector investment from quarters eight to twelve. Computing interim multipliers using Model 5, we find that a one rupee increase in public investment crowds in private investment by 0.30, 1.24, and 1.07 rupees after four, eight, and twelve quarters, respectively. The response of private investment to public infrastructure investment shocks (last graph) is very similar to the case when aggregate public investment is considered (second graph, last row).

Overall, there is evidence for "crowding in" of private investment by public investment, once we restrict the sample post 1980. Similar responses of private investment to a public capital accumulation shock over Models 3, 4, 5, and 6 suggest that public investment has been complementary to the activities of the private sector over both 1980-2012 or 1996Q2-2015Q1 periods. In retrospect, the crowding in finding is not very surprising given the huge infrastructure deficit in India, but it has not been usually found previously in the Indian empirical literature, see Mitra (2006) and Serven (1999). Furthermore, the standard arguments for crowding out (assuming that the economy is operating on its production possibility frontier and has developed financial markets) do not appear to hold for emerging market economies like India. In fact, the crowding out of private investment by public investment over the full sample is likely a reflection of a state-led, inward-oriented growth strategy that existed before the 1980s, which was not supportive of private sector investment.

V. Concluding remarks

Acknowledging the importance of key structural changes that happened in the Indian economy during 1980s and early 1990s, and their potential impact on the relationship between public and private investment, we estimated a variety of SVECMs over different sample periods and frequencies to examine the presence or absence of investment crowding in (out) in India. We embedded (and tested) a long-term relationship between output, public and private investment (motivated by the stationarity of the "great ratio" of aggregate investment and output). We used the properties of the theory-driven long-term relationship to decompose the structural innovations into those with permanent and temporary effects and to identify the

SVECMs. We found public investment "crowded out" private investment in India over the period 1950-2012. In contrast, we found support for crowding in of private investment over the more recent period of 1980-2012. This change in the relationship can be attributed to the policy reforms which started during early 1980s and gained momentum after the 1991 Indian balance of payments crisis. This finding of crowding in is further supported by our quarterly model (estimated over 1996Q2-2015Q1), using project announcements as recorded by CapEx-CMIE database. Future research can exploit our novel micro dataset of public and private investment at quarterly frequency to further disentangle the region- or sector-wise relationship between public investment and private investment in India. For example, one could examine whether states with policies that are more conducive to private investment observed more crowding-in. This will have implications for the design of macroeconomic policies at the level of states or central government.

APPENDIX A

In the spirit of the famous "Great Ratios" suggested by Klein and Kosobud (1961) in the context of economic growth, we can express the long-term relationship between investment and output as

$$i_t - y_t = \kappa + z_t \tag{5}$$

where i_t and y_t represent total investment (public + private) and output respectively. Both variables are in per capita terms and are expressed in logs. The right-hand side of Equation (5) contains a constant and a mean zero I(0) random variable. Express total investment (in levels) as:

$$I_t = I_{pt} + I_{gt} \tag{6}$$

where I_{pt} and I_{gt} represent the total public and private investment at time t, respectively. Dividing equation (6) by I_{gt} and log-linearizing using first-order Taylor expansion yields

$$i_t = \tau + \beta_1 i_{gt} + \beta_2 i_{pt} \tag{7}$$

where small letters denote variables in logs. Coefficients $\beta_1 = c/(1+c)$ and $\beta_2 = 1/(1+c)$ are both less than one, and $c = \exp(i_g - i_p)$ can be understood as the average ratio of public to private investment in the economy. τ is a linearization constant which equals $\ln(1+c) - c\ln(c)/(1+c)$. We can use Equations (5) and (7) to express a long term relationship between public investment, private investment, and output as follows:

$$\beta_1 i_{gt} + \beta_2 i_{pt} - y \approx \kappa + z_t \tag{8}$$

which ignores the constant of linearization.

APPENDIX B

Unit root tests

We first determine the order of integration of the variables y_t, gi_t, pi_t, and gi_t^{infr} over the period 1950-2012. We report the results from the Augmented Dickey-Fuller (ADF) test, ADF-GLS test as proposed by Elliott et al. (1996), and Phillips-Perron (PP) unit root test. All three tests have a null hypothesis of individual series being a random walk against the alternative of stationarity. To preserve uniformity across tests, we select the lag order for a variable based on Ng–Perron modified Akaike information criterion (MAIC) as reported in the ADF-GLS test. Since all variables, when expressed in levels, appear to be trending, all tests on the level of variables include a deterministic time trend.[20] The results are reported in the first panel of Table 1. They indicate that we cannot reject the null of non-stationarity even at 10% level, while all the tests on the first-differenced variables strongly reject the presence of a unit root at 1% significance level. We therefore conclude that all four variables are integrated of order 1 or I(1).[21] Similarly, all variables are shown to be integrated of order one over the smaller sub-sample from 1980 (panel 2). Finally, we test for unit roots in quarterly series where we have two variants of public and private investment, as discussed in the data section. For all variables, the null of a unit root cannot be rejected even at 10% level of significance, while all variables except pi_1 and pi_2 clearly reject the null of a unit root in first differences. Although for pi_1 and pi_2, the null of unit root cannot be rejected in first differences for ADF test, the Phillips–Perron test strongly rejects the null at the 1% level. We therefore continue to treat pi_1 and pi_2 as I(1).

Cointegration rank tests

Table 2 reports the lag order and the number of cointegrating vectors used in various VECM models discussed in the paper. For all specifications using annual data, a VECM order of 0 (in first differences) is selected based on the Akaike Information Criterion.[22] Models 1 and 2, which are based on the full sample data confirm the presence of one cointegrating vector based on 99% trace test statistic. Although Model 3 does not confirm the presence of any cointegration between the three variables, this may be due to the loss of power of the test over a small sample of around 30 annual observations. For robustness, we conduct the Johansen trace test with structural break as discussed in Johansen et al. (2000) where we take y_t, gi_t, and pi_t over the whole sample, but allow for breaks in level and trend at 1980. The test

[20] No trend is included in the tests on first-differenced variables.

[21] As a robustness check to our unit root tests, we also conducted the Clemente et al. (1998) unit root test, which allows for one or two structural breaks in the series being tested for non-stationarity. Our results (available on request) are robust to this additional test.

[22] Maximum number of lags were set to two years.

strongly supports the evidence of one cointegrating vector. The results do not change even if we allow for a second break in 1991. Hence, we continue to estimate a VECM with one cointegration rank in Model 3. For VECMs using quarterly data, a lag order of 7 (in first differences) is selected based on the Akaike Information Criterion.[23] Models 4 and 6, using quarterly data, support the presence of one cointegrating relation between the three variables. Model 5 indicates the presence of two cointegrating vectors. However, we continue to proceed with one cointegrating rank which is also confirmed by maximum eigen value test statistic at the same significance level (not reported in the paper but available upon request).

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[23]Only for Model 6, AIC reports lag of 8, while FPE reports lag order 6. To maintain uniformity of lags across models 4, 5, and 6, we continue to choose lag 7 as before. Results are invariant to the inclusion of lag order 8 for model 6.

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Table 1. **Unit Root Tests**

Annual Data 1950-2012

	y	gi	pi	gi^{infra}
ADF	1.15	-2.98	-0.31	-1.23
ADF-GLS	0.16	-1.61	-0.76	-1.30
PP	1.02	-2.55	-1.28	-0.86
	Δy	Δgi	Δpi	Δgi^{infra}
ADF	-6.88^{***}	-5.66^{***}	-4.40^{***}	-6.35^{***}
ADF-GLS	-6.54^{***}	-5.70^{***}	-2.39^{**}	-6.00^{***}
PP	-6.88^{***}	-5.71^{***}	-7.81^{***}	-6.35^{***}

Annual Data 1980-2012

	y	gi	pi
ADF	-0.58	-0.53	-2.07
ADF-GLS	-0.68	-0.85	-1.49
PP	-0.37	-0.47	-3.02
	Δy	Δgi	Δpi
ADF	-4.32^{***}	-4.48^{***}	-3.66^{**}
ADF-GLS	-4.40^{***}	-4.45^{***}	-3.63^{**}
PP	-4.32^{***}	-4.48^{***}	-6.98^{***}

Quarterly Data 1996Q2-2015Q1

	y	gi_1	pi_1	gi_2	pi_2	gi_2^{infra}
ADF	-1.99	-2.32	-2.70	-1.71	-2.46	-1.38
ADF-GLS	-1.27	-1.86	-2.10	-1.09	-1.89	-1.37
PP	-2.47	-1.42	-1.66	-1.45	-1.83	-1.96
	Δy	Δgi_1	Δpi_1	Δgi_2	Δpi_2	
ADF	-9.14^{***}	-2.81^{*}	-2.01	-6.20^{***}	-2.06	-0.80
ADF-GLS	-4.54^{***}	-2.82^{***}	-1.97^{*}	-6.11^{***}	-1.73	-3.77^{***}
PP	-9.14^{***}	-5.82^{***}	-4.72^{***}	-6.20^{***}	-5.72^{***}	-6.37^{***}

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. ADF denotes the Augmented Dickey-Fuller Test, ADF-GLS the generalized least squares version of the ADF test, and PP the Phillips-Perron test. Trend and intercept are included as deterministic terms in tests with level variables while only intercept is included in tests with differenced variables. For each variable, the number of lags are selected on Ng–Perron modified Akaike information criterion (MAIC) as reported in ADF-GLS.

Table 2. Lag Orders and Cointegrating Rank of the VECMs

Annual Data	VECM Order*	Cointegrating relations
Model 1: $(y, gi, pi)'$	0	1
Model 2: $(y, gi^i, pi)'$	0	1
Model 3: $(y, gi, pi)'_{1980}$	0	0
Quarterly Data	**VECM Order***	**Cointegrating relations**
Model 4: $(y, gi_1, pi_1)'$	7	1
Model 5: $(y, gi_2, pi_2)'$	7	2
Model 6: $(y, gi_2^{\text{infra}}, pi_2)'$	7	1

Notes: * denotes lag order in first differences selected by the Akaike Information Criterion, with the maximum lag orders set to 2 in models with annual data and 8 in models with quarterly data (see Appendix B for details). Selection of the number of cointegrating relations is based on the trace test statistics calculated at 99% critical values.

Table 3. **Loading Coefficients and Cointegrating Vectors**

	$\boldsymbol{\alpha}'$	$\boldsymbol{\beta}'$
Annual Data		
Model 1: $(y, gi, pi)'$	$\begin{pmatrix} 0.001 & 0.76^{***} & 0.71^{***} \end{pmatrix}$	$\begin{pmatrix} 1 & -0.12^{***} & -0.44^{***} \end{pmatrix}$
Model 2: $(y, gi^i, pi)'$	$\begin{pmatrix} 0.16^{**} & 0.70^{***} & 0.90^{***} \end{pmatrix}$	$\begin{pmatrix} 1 & -0.20^{***} & -0.35^{***} \end{pmatrix}$
Model 3: $(y, gi, pi)'_{1980}$	$\begin{pmatrix} -0.11 & -0.52^{**} & 0.76^{**} \end{pmatrix}$	$\begin{pmatrix} 1 & -0.13^{*} & -0.65^{***} \end{pmatrix}$
Quarterly Data		
Model 4: $(y, gi_1, pi_1)'$	$\begin{pmatrix} -0.74^{***} & -0.10 & 1.73^{**} \end{pmatrix}$	$\begin{pmatrix} 1 & 0.07^{**} & -0.12^{***} \end{pmatrix}$
Model 5: $(y, gi_2, pi_2)'$	$\begin{pmatrix} -0.25^{***} & 0.15 & 0.97^{***} \end{pmatrix}$	$\begin{pmatrix} 1 & -0.03 & -0.13^{***} \end{pmatrix}$
Model 6: $(y, gi_2^{\text{infra}}, pi_2)'$	$\begin{pmatrix} -0.24^{***} & 0.37^{**} & 0.99^{***} \end{pmatrix}$	$\begin{pmatrix} 1 & -0.03 & -0.13^{***} \end{pmatrix}$

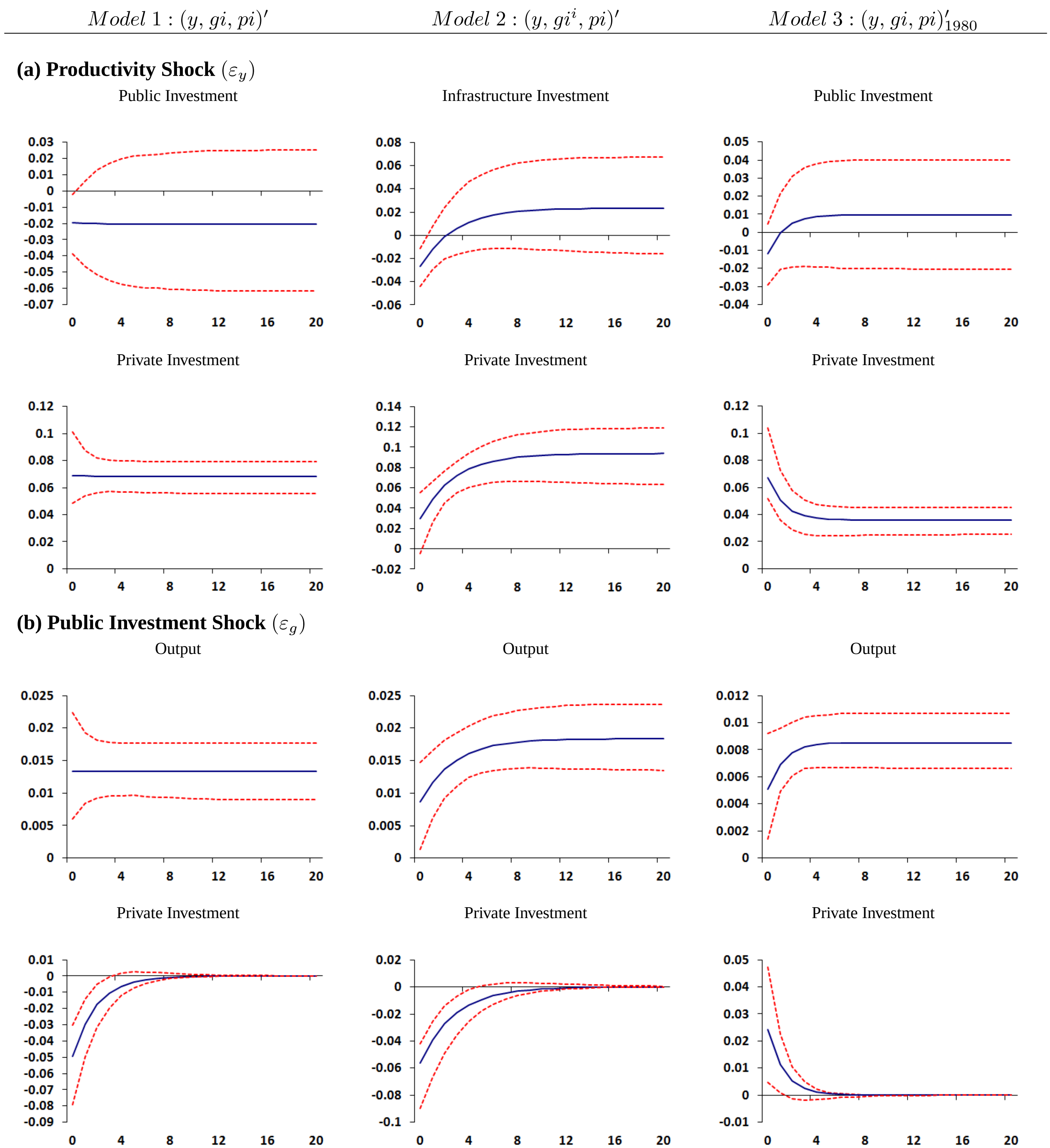
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4. **Short and Long Run Matrices**

	$\mathbf{B}$	$\Xi\mathbf{B}$
Annual Data		
Model 1: $(y, gi, pi)'$	$\begin{pmatrix} 0.03^{***} & 0.01^{***} & 0.00 \\ -0.02 & 0.06^{***} & 0.04^{***} \\ 0.07^{***} & -0.05^{***} & 0.04^{***} \end{pmatrix}$	$\begin{pmatrix} 0.03^{***} & 0.01^{***} & 0 \\ -0.02 & 0.11^{***} & 0 \\ 0.07^{***} & 0 & 0 \end{pmatrix}$
Model 2: $(y, gi^i, pi)'$	$\begin{pmatrix} 0.03^{***} & 0.01^{*} & 0.01^{***} \\ -0.03^{**} & 0.05^{***} & 0.05^{***} \\ 0.03 & -0.06^{***} & 0.06^{***} \end{pmatrix}$	$\begin{pmatrix} 0.04^{**} & 0.02^{***} & 0 \\ 0.02 & 0.09^{***} & 0 \\ 0.09^{***} & 0 & 0 \end{pmatrix}$
Model 3: $(y, gi, pi)'_{1980}$	$\begin{pmatrix} 0.02^{***} & 0.01^{**} & -0.01^{**} \\ -0.01 & 0.05^{***} & -0.03^{***} \\ 0.07^{***} & 0.02^{**} & 0.04^{***} \end{pmatrix}$	$\begin{pmatrix} 0.02^{***} & 0.01^{***} & 0 \\ 0.01 & 0.07^{***} & 0 \\ 0.04^{***} & 0 & 0 \end{pmatrix}$
Quarterly Data		
Model 4: $(y, gi_1, pi_1)'$	$\begin{pmatrix} 0.01^{***} & -0.00 & -0.01 \\ 0.01 & 0.02 & -0.00 \\ 0.04^{***} & -0.01 & 0.02 \end{pmatrix}$	$\begin{pmatrix} 0.01 & -0.002^{**} & 0 \\ 0.07 & 0.02^{**} & 0 \\ 0.16 & 0 & 0 \end{pmatrix}$
Model 5: $(y, gi_2, pi_2)'$	$\begin{pmatrix} 0.01^{***} & 0.00 & -0.01^{***} \\ -0.01 & 0.02^{***} & 0.00 \\ 0.03^{***} & 0.00 & 0.02^{***} \end{pmatrix}$	$\begin{pmatrix} 0.02 & 0.001^{**} & 0 \\ 0.03 & 0.03^{**} & 0 \\ 0.11 & 0 & 0 \end{pmatrix}$
Model 6: $(y, gi_2^{\text{infra}}, pi_2)'$	$\begin{pmatrix} 0.001^{***} & 0.01^{***} & -0.01^{***} \\ -0.01^{***} & 0.02^{***} & 0.01^{***} \\ 0.03^{***} & 0.01 & 0.02^{***} \end{pmatrix}$	$\begin{pmatrix} 0.02 & 0.002^{***} & 0 \\ 0.03 & 0.02^{***} & 0 \\ 0.13 & 0 & 0 \end{pmatrix}$

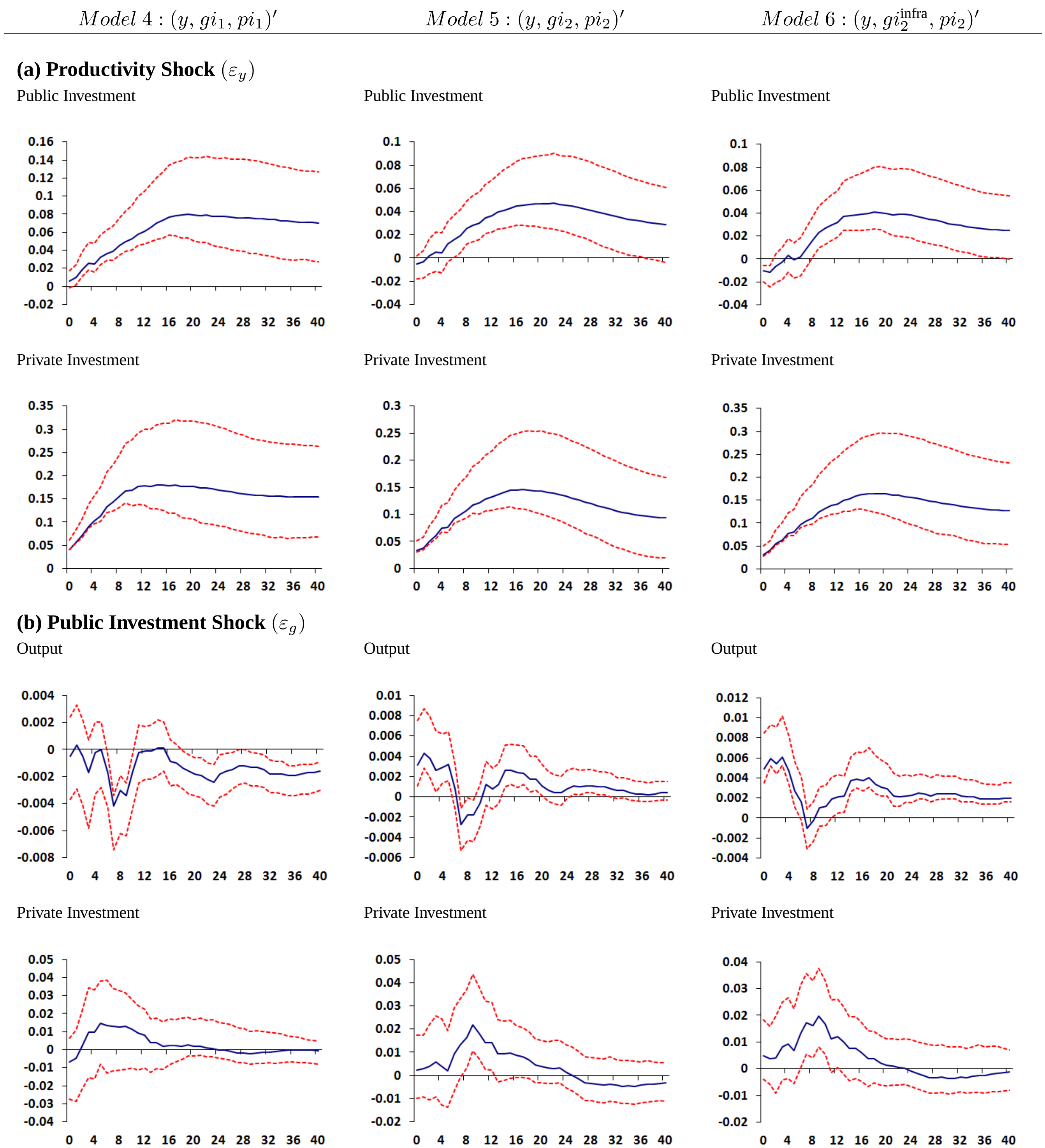
${}^{*}p < 0.1$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$.

Figure 1. **Structural Impulse Responses to Productivity and Public Investment Shocks (Annual)**



Notes: Figures are impulse responses to a one standard deviation shock to productivity or government investment, together with the 5th and 95th percentile bootstrapped error bands with 2000 replications. Columns 1 and 3 correspond to our baseline specification which includes output, public investment, and private investment over 1950-2012 and 1980-2012 periods, respectively. Model in column 2 is similar to that in column 1 except that we consider public infrastructure investment instead of total public investment.

Figure 2. **Structural Impulse Responses to Productivity and Public Investment Shocks (Quarterly)**



Notes: Figures are impulse responses to a one standard deviation shock to productivity or public investment, together with the 5th and 95th percentile bootstrapped error bands with 2000 replications. The impulse responses correspond to models with quarterly data on public and private investment projects constructed from CAPEX-CMIE database. Columns 1, 2, and 3 show impulse responses of models 4, 5, and 6, respectively. In model 4, shelved or abandoned projects (for both public and private sectors) are not included in the construction of the investment series once they are shelved or abandoned. Model 5 considers the other extreme where shelved or abandoned projects are not excluded from the investment series altogether from the date of announcement. Model 6 takes public investment as constructed in Model 4 and private investment as in Model 5.