New Evidence on the FDI-Led Growth: The Case of China

A. Yasemin Yalta

October 2011
New evidence on the FDI-led growth: The case of China

A. Yasemin YALTA*

Hacettepe University, Department of Economics, 06800, Ankara, Turkey

Abstract

We employ simulation based inference to investigate the causal relationship between foreign direct investment and gross domestic product in China for the 1982-2008 period, both in a bivariate and a multivariate framework. Our maximum entropy bootstrap based approach, which avoids pre-test biases while also being less affected from the size distortion problem, shows that a statistically significant relationship between FDI and GDP growth does not exist. This result indicates that FDI does not necessarily lead to higher economic growth at the aggregate level and suggests the need for undertaking a disaggregated analysis using industrial and provincial level data for the formulation of effective macroeconomic policies concerning the flows of FDI.

JEL classification: F21, F43, C5

Key words: FDI; Economic growth; China; Bootstrap.

1. Introduction

* E-mail: yyalta@hacettepe.edu.tr
Since the early 1990s, China has seen large inflows of foreign direct investment (FDI) and has become one of the biggest recipients of FDI among the developing countries. Indeed, while FDI to China totaled $321 billion between 1990 and 2000, this amount increased to about $638 billion between 2000 and 2008. Consequently, it is important, both theoretically and practically, to understand whether these resource flows have contributed to higher growth rates in China.

In theory, the causal relation between FDI and GDP growth can run in either direction. On the one hand, according to the “FDI-led growth hypothesis”, FDI inflows can stimulate growth for the host countries by increasing the capital stock, creating new job opportunities, and easing the transfer of technology (de Mello, 1997; Borensztein, 1998; De Gregorio, 2003). On the other hand, according to the “market size hypothesis”, rapid GDP growth creating new investment opportunities in the host country can also cause larger inflows of FDI (Rodrik, 1999; Mah, 2010). In addition, although the existing studies generally suggest a positive impact of FDI on economic growth, it is also possible that FDI has negative effects on economic growth because it crowds out domestic investment, increases external vulnerability and dependence (Aitken and Harrison, 1999; Lipsey, 2002). Last but not least, it is also possible that a causal relationship between FDI and economic growth does not exist, supporting the so-called “neutrality hypothesis”.

Although the possible causal linkage between FDI and economic growth in China has been a subject of considerable research in the recent years, empirical findings so far have provided conflicting predictions about the growth effects of FDI. There are at least three studies which report causality running from FDI to GDP. Dees (2001), running simulations on quarterly data, showed that FDI has a positive long-run effect on output between 1984 and 1995 in China. Tang et al. (2008) focused on the 1988-2003 period and, using a cointegration and Granger causality analysis, found causality running from FDI to GDP. Chen et al. (1995)
also concluded that FDI has been positively associated with higher growth rates between 1970 and 1990. Notwithstanding, there also exists empirical evidence pointing out causality running from GDP to FDI. Using a small sample cointegration test, Mah (2010) examined the causality between FDI and GDP growth for the 1983-2001 period, and concluded that causality runs from GDP to FDI. Using the VAR approach developed by Toda and Philips, Zhao and Du (2007) also concluded that China’s economic growth has attracted FDI inflows. Finally, there are also studies that report causality running in both directions. Employing a vector autoregression (VAR) approach in the production function context, and using the Toda and Yamamoto's Granger no-causality testing procedure, Shan (2002) and Shan et al. (2004) found a two-way causality running between output and FDI flows for the period between 1986 and 1998. Xiaohui et al. (2002) also employed a cointegration framework and found a bi-directional causality between economic growth and FDI.

Understanding which of the above propositions is valid for China's case is important for the formulation of effective macroeconomic policies concerning the flows of FDI into the country. If the “FDI-led growth” hypothesis holds, then China should encourage FDI inflows with continued support for various types of tax and financial incentives. However, if causality is running from economic growth to FDI, rather than offering further incentives and privileges to foreign investors, priority should be given to factors such as domestic investment, which might have been more important in explaining the rapid economic growth in China (See Tang et al., 2008; Chen and Feng, 2000). Due to the inconsistency of the existing findings, however, it is currently difficult to recommend a reliable policy direction for China. The contradicting results arise because of the evolutionary nature of time series data as well as the limited number of observations, which cause empirical results to vary based on the time period and the econometric methodology considered. One cannot help but notice that most of the time series studies on FDI and GDP growth are based on the traditional cointegration
procedure developed by Johansen (1995) as well as standard causality testing. It is long known that this approach is sensitive to wrongly finding a statistically significant relationship due to rejecting the true null hypothesis in small samples (Zhou, 2007; Herzer et al., 2008; Yalta, 2010). In response to the growing number of controversial results, authors such as Herzer et al. (2008), among others, have argued that rather than employing the usual methods, newer techniques that do not suffer from small-sample bias need to be considered to assess the robustness of the earlier results.

In this study, we re-examine the FDI-led growth hypothesis for China by using state of the art bootstrap inference based on the maximum entropy bootstrap (meboot) technique. It is well established that simulation based hypothesis testing can yield substantially more accurate results in small samples in comparison to conventional inferences based on asymptotic theory (MacKinnon, 2007). However, to our knowledge, bootstrapping has never been employed to examine the causal relationship between FDI and GDP growth. Developed by Vinod (2004), meboot is a particularly attractive bootstrap data generation process (DGP) for the analysis of time series data because it can be employed in all forms of structural breaks and nonstationarity without transforming the data. This in turn helps avoid pre-testing led specification errors and allows more robust and accurate statistical inferences. As a result, we aim to contribute to the literature by employing this advanced technique to provide robust and conclusive results regarding the causal relationship between FDI and GDP in China. Our paper also differs from various earlier studies in the sense that, in addition to testing the usual bivariate relationship between FDI and growth, we also employ a multivariate approach to overcome a possible omitted variable bias problem. An econometric specification that includes gross capital formation and labor force as additional variables can help better capture the dynamic relationship between FDI and GDP growth.
Our findings, which are robust to different specifications, indicate that there is no statistically significant relationship between FDI and economic growth in China. This result, which contradicts with some of the previous studies, suggests that FDI may not lead to higher growth rates at the aggregate level as the effects of FDI may be dissipated at the disaggregate level. This, in turn, points out the need for future research focusing on the FDI-GDP relationship at the industrial and provincial level.

The rest of the paper is organized as follows: Section 2 provides a brief theoretical overview of FDI flows to China; Section 3 explains our methodology, describes the data, and presents the empirical results. Finally, Section 4 concludes by discussing some of the policy implications of our findings.

2. An Overview of the FDI Inflows to China

Prior to 1978, FDI inflows to China has been low because of the inward oriented economic policies. After the adoption of the “opening-up” policies in 1979, which granted foreign investment a legal status in China, the country began to attract increasing flows of FDI. In the early 1980s, special economic zones were established and special privileges such as tax reductions and factor input concessions were granted to foreign investors. However, as can be seen in Table 1, the amount of FDI inflows were still unsubstantial during the 1980s. The major increases in the FDI volume occurred after 1992, when China began to strengthen the market economy with the famous “Southern Trip” by the Chinese leader Deng Xiaoping. In 1993, China became the largest recipient of FDI among the developing countries for the first time. The Chinese government further liberalized the FDI policy in late 1997 by introducing various measures such as abolition of the FDI project approval requirements as well as reductions in import tariffs. In the late 1990s, there was a small decrease in FDI inflows where the average annual growth rate of FDI remained approximately 3 percent.
between 1998 and 2001. Chinese membership to World Trade Organization in 2001 marked the turning point in FDI flows to China, and FDI inflows quickly increased to over 10 percent per annum. In the three consecutive years, China registered FDI growth of 15, 13, and 14 percent respectively.

### Table 1: Average FDI inflows (% of GDP) and Growth Rates

<table>
<thead>
<tr>
<th>Years</th>
<th>FDI, net inflows (% of GDP)</th>
<th>GDP growth (annual %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982-1985</td>
<td>0,38</td>
<td>12,18</td>
</tr>
<tr>
<td>1986-1989</td>
<td>0,88</td>
<td>8,95</td>
</tr>
<tr>
<td>1990-1993</td>
<td>2,75</td>
<td>10,3</td>
</tr>
<tr>
<td>1994-1997</td>
<td>5,08</td>
<td>10,83</td>
</tr>
<tr>
<td>1998-2001</td>
<td>3,6</td>
<td>8,03</td>
</tr>
<tr>
<td>2002-2005</td>
<td>3,15</td>
<td>10,13</td>
</tr>
<tr>
<td>2006-2009</td>
<td>3,41</td>
<td>13,45</td>
</tr>
</tbody>
</table>

Source: World Development Indicators, 2010

Since the economic reforms in 1978, China’s growth performance has been remarkable. As Table 1 reveals, annual average real GDP growth rate was 10 percent between 1982 and 2009, making the country one of the fastest growing economies in the world. Many economists assert that FDI has been a driving force behind China’s high growth rates. In the recent years, however, it is frequently argued that the contribution of FDI to high growth rates at the aggregate level has actually been much lower than expected. For example, an important feature of FDI in China, not visible in the table, is the unequal distribution of FDI among different regions and industries. FDI has poured into the Eastern and coastal regions since the open door policy, while less attention is given to the Western regions (Ran et al., 2007). 12 coastal provinces out of 31 provinces in China host nearly 90 percent of total FDI inflows. (Laurenceson and Tang, 2007). Due to the significant differences across provinces and industries in terms of the distribution of FDI, the overall effect of FDI becomes questionable.

---

1 For a more detailed account of China's recent experience regarding FDI flows, the reader is referred to Chen et al. (1995), Shan et al. (2004).
at the aggregate level (Ran et al., 2007; Braunstein and Epstein, 2002). In addition, Mah (2010) argues that there is no strict positive relation between FDI and economic growth because, although average annual FDI inflows were at very low levels between 1982 and 1989, the growth rates were very impressive during the same period. Furthermore, there are also growth-accounting studies which indicate that once other relevant factors such as human capital and infrastructure are accounted for, the effect of FDI seems lower (Laurenceson and Tang, 2007), whereas domestic sources such as capital accumulation become more important (Cheung and Lin, 2004). These controversial findings point out the need for the reassessment of the relation between FDI and GDP growth in China using newer and more robust econometric tools.

3. Methodology and Data Issues

In the time series literature, it is common to assess the direction of causality between two variables using the Granger causality tests. Although Granger tests can yield some valuable information in terms of time patterns, they are also known to have certain disadvantages. For example, standard Granger-causality tests may have non-standard asymptotic properties if the variables considered in a VAR specification are integrated or cointegrated (Philips, 1987; Toda and Philips, 1993). Moreover, in causality testing, there is also a high risk of wrongly finding a statistically significant relationship due to rejecting the true null of no causality (Yalta, 2010). These problems can be alleviated to a large extent using simulation based bootstrap distributions for statistical inference. In general, bootstrapping involves constructing a simulated empirical distribution function by using a parametric method or resampling for a large number of simulated values of an observed test statistic and. For example, in the basic parametric IID bootstrap (Efron 1982), simulated error vectors are created by random resampling a large number of times the residuals from the fitted model. These are
subsequently plugged into the original model for regression and the computation of confidence limits for the required test statistic. It is documented by various authors that the bootstrap technique has less size distortion and provides more precise test inferences than the standard asymptotic analyses, especially when the sample size is small (See Mantalos, 2000; Horowitz, 2003). Thus, various researchers have developed different bootstrap alternatives suitable for using with time series data, such as the block bootstrap, the sieve bootstrap as well as meboot.

Introduced by Vinod (2004), meboot is the most recent and one of the most advanced bootstrap data generation processes, specifically designed to avoid the problems of the traditional bootstrap methods Vinod (2004, 2006). In alternative bootstrap methods such as the block bootstrap, an important limitation is the reordering of the original data, which distorts their dependence and heterogeneity information (Koutris et al., 2008). The meboot DGP can avoid this problem by employing a seven-step algorithm, which creates replicates retaining the basic shape and dependence structure of the autocorrelation function and the partial autocorrelation function of the original data. It is proven that the process satisfies the ergodic theorem as well as the central limit theorem (Vinod and Lacalle, 2009). This means that, as the sample size increases, a statistical test run on a replicate will result in p-values converging to that of the original series. By creating a large number of such replicates, one can construct numerical sampling distributions for many pivotal statistics without having to know their possibly multimodal and nonnormal functional forms (Vinod, 2003). The main advantage of this method is that unit root testing, differencing or ARMA transformations can be avoided altogether since ensemble confidence intervals are robust. This in turn permits more flexible and reliable empirical analysis and therefore can be used in all forms of nonstationarity.²

² For more information on the meboot technique, see Vinod (2006) and Vinod and Lacalle (2009).
3.1. Bivariate Analysis

We start our investigation of the possible linkage between FDI and growth in China by first considering the following VAR system in a bivariate framework

\[ y_t = c_1 \sum_{i=1}^{n} \alpha_{1i} FDI_{t-i} + \sum_{j=1}^{n} \beta_{1j} y_{t-j} + u_{1t} \]  

(1)

\[ FDI_t = c_2 \sum_{i=1}^{n} \alpha_{2i} FDI_{t-i} + \sum_{j=1}^{n} \beta_{2j} y_{t-j} + u_{2t} \]  

(2)

where \( u_1 \) and \( u_2 \) are the residual terms, \( c_1 \) and \( c_2 \) are the constant terms, \( y \) is the log of real GDP, and \( FDI \) is the log of FDI inflows. The annual data on GDP and FDI between 1982-2008 are obtained from World Development Indicators (2010). Both series are deflated using the GDP deflator with 2000 as the base year. Figure 1 provides a plot of the two variables.

![Figure 1: Plot of the log of real FDI and the log of real GDP](image)
Because the meboot technique can be seamlessly applied under all sorts of non-stationarity, testing for unit roots and cointegration is not germane to our analysis.\footnote{See Vinod and Lacalle (2009) and Yalta (2010) for a detailed discussion.} For the causality testing procedure, we employ the meboot algorithm and first create two resamples \(y_{j,t}\) and \(FDI_{j,t}\) for \(j = 1, \ldots, J\) (\(J = 999\)) of both series. The resulting “ensemble”, denoted by \(\Omega\), represents the population of the original data, which we employ to run \(J\) regressions for Equations (1) and (2). The quantiles of the 999 coefficient estimates for each parameter are subsequently used to obtain the confidence limits for \(\alpha_{1i}\) and \(\beta_{2j}\). Following Vinod and Lacalle (2009) and Yalta (2010), the confidence limits are computed using the Highest Density Region (HDR) method discussed by Hyndman (1996). The HDR approach determines confidence limits by requiring them to contain points of relatively high density, which is especially useful for our analysis where nonstandard distributions is a possibility. Once the confidence limits are determined for the individual coefficients, the null hypothesis that \(FDI\) does not cause \(y\) (\(y\) does not cause \(FDI\)) is rejected if zero remains outside the \(1 - \alpha\) 100\% confidence interval for \(\alpha_{1i}\) (\(\beta_{2j}\)).

The results of bivariate analysis are shown in Table 2. On the left panel of the table, we present meboot based HDR confidence limits for \(\alpha = 0.05\) and the lag order \(n = 1\). It is seen that zero is found inside the 95\% confidence intervals for both the \(\alpha_{1,1}\) and the \(\beta_{2,1}\) coefficients. As a result, the null of no causality cannot be rejected for both directions. On the right panel of the table, meboot based 90\% HDR confidence limits are provided for the lag order \(n = 2\). The reason for \(\alpha = 0.1\) here is that our bootstrap confidence limits do not accommodate the classic Wald test approach to test for the joint null hypothesis that the coefficients of the cause variables are zero simultaneously. Instead, we employ the well-known Bonferroni inequality, which requires setting \(\alpha' = \alpha/m\) when there are \(m\) tests being
performed at the same time. Because zero is found inside the 90% confidence limits for both lags of FDI in the GDP equation, we do not reject the null that FDI does not Granger cause GDP at the $\alpha = 0.05$ level. The similar result is found for the FDI equation as well. In addition, we see that GDP and FDI are Granger caused by their respective first lags, indicating that both FDI and growth has been self-reinforcing during the sample period.

Table 2: Bivariate Analysis Using 90 % and 95 % Confidence Levels

<table>
<thead>
<tr>
<th>VAR(1) MEBOOT 95% CONFIDENCE INTERVALS</th>
<th>VAR(2) MEBOOT 90% CONFIDENCE INTERVALS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log of RGDP</td>
<td>Log of FDI</td>
</tr>
<tr>
<td>Lower</td>
<td>Upper</td>
</tr>
<tr>
<td>Constant</td>
<td>-0,961</td>
</tr>
<tr>
<td>RGDP(-1)</td>
<td>0,838</td>
</tr>
<tr>
<td>FDI(-1)</td>
<td>-0,045</td>
</tr>
<tr>
<td>RGDP(-2)</td>
<td>0,066</td>
</tr>
<tr>
<td>FDI(-2)</td>
<td>-110,26</td>
</tr>
</tbody>
</table>

For both VAR(1) and VAR(2) estimations; the Akaike, Schwarz, and Hannan-Quinn criteria are found similar. The results are robust in showing no causal relationship between FDI and GDP in the bivariate analysis. This may not be surprising given that a visual inspection of the data in Figure 1 also reveals no sign of precedence between the two variables.

3.2. Multivariate Analysis

Although most studies on the causal nexus between FDI and GDP employ a bivariate framework, the relation between the two can be affected by other variables such as industrial output, labor force, capital expenditure, financial market development, and degree of
openness (Riezman et al., 1996; Shan, 2002). Because the failure to take into account important external factors can result in a specification bias, we extend our analysis into a multivariate framework. Following Shan (2002), and Balasubramanyam et al. (1996), we consider the endogenous nature of the production function and include in the multivariate analysis two explanatory variables namely gross fixed capital formation and labor force.4 It is documented in the literature (de Mello, 1997) that in evaluating the FDI-growth nexus, the link between foreign and domestic investment constitutes the key point due to the importance of a strong domestic investment climate in attracting foreign capital. It is also possible that FDI complements or substitutes domestic investment. The second variable we consider is the labor force, which is also preferred in various earlier studies such as Balasubramanyam et al. (1996), Shan (2002), and Shan et al. (2004).

With the inclusion of the additional variables, our model specifications become

\[
y_t = c_1 + \sum_{i=1}^{n} \alpha_{1i} FDI_{t-i} + \sum_{i=1}^{n} \beta_{1i} y_{t-i} + \sum_{i=1}^{n} \gamma_{1i} e_{t-i} + \sum_{i=1}^{n} \lambda_{1i} r_{t-i} + v_{1t}
\]

\[
FDI_t = c_2 + \sum_{i=1}^{n} \alpha_{2i} FDI_{t-i} + \sum_{i=1}^{n} \beta_{2i} y_{t-i} + \sum_{i=1}^{n} \gamma_{2i} e_{t-i} + \sum_{i=1}^{n} \lambda_{2i} r_{t-i} + v_{2t}
\]

where \(e\) is the log of labor force, and \(r\) is the log of real gross fixed capital formation (2000 base year). The additional series are obtained from World Development Indicators (2010) as well.

Table 3 shows the causality test results for the multivariate analysis based on meboot and the HDR 95% and 90% confidence limits when the lag order is \(n=1\) and \(n=2\) respectively. Once again, it is seen in the table that zero is found inside the 95% and 90% confidence intervals for both the \(\alpha_{1,1}\) and the \(\beta_{2,1}\) parameters. As a result, after controlling for

---

4 Variables other than those included in the model are also a possibility. However, because of data limitations and the concern for degree of freedom, we consider gross fixed capital formation and labor force.
investment and labor force, we obtain robust and consistent results supporting the neutrality hypothesis between FDI and GDP one more time. The first lag of GDP is significant in the multivariate framework as well, showing that current output growth can influence future trends of GDP growth. It is also worth noting that the Akaike, Schwarz, and Hannan-Quinn criteria are improved in multivariate analysis, which points out the importance of a multivariate approach for the investigation of the causal nexus between growth and FDI.

Several reasons might account for the rejection of a growth-inducing effect of FDI in China. One explanation is that growth limiting effects of FDI offsetting the growth-enhancing effects leading to a small or no net effect (Herzer et al., 2008). In addition, Huang (1998, 2003) argues that foreign investment in China substitutes domestic investment as foreign invested enterprises exploit the preferential policies given to foreign firms and compete for local scarce resources. Braunstein and Epstein (2002) also point out that foreign investment crowds in domestic investment because social benefits of FDI are dissipated at the provincial level due to the intense competition for FDI among different regions. Ran et al. (2007) suggest that China does not appear to benefit from FDI at the aggregate level because relatively more developed coastal regions gain more from FDI while the provinces in western and central regions lose.

| Table 3: Multivariate Analysis Using 90 % and 95 % Confidence Levels |
|-------------------|-------------------|-------------------|-------------------|
|                   | VAR(1) MEBOOT 95% CONFIDENCE INTERVALS | VAR(2) MEBOOT 90% CONFIDENCE INTERVALS |
|                   | Log of RGDP       | Log of FDI        | Log of RGDP       | Log of FDI        |
| Constant          | -31,346           | 21,095            | -190,274          | 70,004            |
|                   | -36,577           | 21,875            | -215,313          | 82,306            |
| RGDP(-1)          | 0.418             | 1.108             | 0.269             | 1.125             |
|                   | -2,027            | 2,076             | -2,331            | 2,531             |
| FDI(-1)           | -0.087            | 0.093             | -0.094            | 0.105             |
|                   | -0.087            | 0.922             | -0.177            | 0.830             |
| GFCF(-1)          | -0.113            | 0.378             | -0.224            | 0.373             |
|                   | -1,226            | 1,708             | -1,010            | 1,896             |
| LF(-1)            | -2,785            | 3,339             | -13,660           | 17,834            |
|                   | -2,420            | 2,441             |
| RGDP(-2)          | -0.403            | 0.439             |
|                   | -0.099            | 0.092             |
| FDI(-2)           | -0.0410           | 0.459             |
Finally, Figures 2 and 3 respectively show the HDR intervals for the parameter estimates for the GDP and the FDI equations when \( n=2 \) in the multivariate analysis. The horizontal bars in each plot represent the probability coverage levels 90, 95, and 99 respectively. The plots illustrate that the HDRs, which are narrower than the naive percentile intervals, cover zero for when considering both lags of the variables.

### 4. Conclusion and Policy Implications

Understanding the role played by FDI on economic growth is important for policy makers in China for the formulation of effective macroeconomic policies concerning the flows of FDI into the country. However, the existing empirical studies provide conflicting results on this issue making it difficult to recommend a policy direction. This requires the investigation of this issue using the newest, more robust econometric techniques instead of the usual methods that can suffer from various problems most notably over-rejection due to a small sample.

Using the meboot DGP, which provides an advanced and powerful tool for doing inference using time series data, we investigate the relationship between FDI and economic growth in China for the period between 1982-2008. Our method has the advantage of offering more accurate results in small samples in addition to avoiding shape-destroying transformations under all types of nonstationarity. Adopting this time series methodology to detect causality provides us with more robust conclusions regarding policy guidelines in this research area. In addition, to avoid a possible omitted variable bias, we undertake a
multivariate approach in which we consider two additional variables namely gross capital formation and labor force.

Our findings, which are robust to the choice of the lag order as well as the use of bivariate or multivariate specifications, imply that a statistically significant relation between FDI and economic growth does not exist. This result is in line with some of the previous studies. Görg and Greenaway (2004) argue that the effects of capital accumulation and the positive knowledge spillovers predicted by endogenous growth models may not occur in developing countries due to multinationals trying to protect their firm-specific knowledge. Aitken and Harrison (1999) suggest that foreign firms reduce the productivity of domestic firms through competition effects. Huang (1998, 2003) argues that foreign investment in China substitutes domestic investment as foreign invested enterprises exploit the preferential policies given to foreign firms and compete for local scarce resources. Ran et al. (2007) suggest that China does not appear to benefit from FDI at the aggregate level because relatively more developed coastal regions gain more from FDI while the provinces in western and central regions lose. As a result, our finding has important policy implications for China. Rather than trying to attract more FDI inflows by offering incentives and privileges to foreign investors, priority should be given to factors which might have been more important in explaining rapid economic growth in China such as domestic investment (Tang et al., 2008), private and semiprivate enterprises, and higher education (Chen and Feng, 2000).

Future research in this area should focus on two issues: First, in our analysis, which is undertaken at the aggregate level, FDI does not contribute to higher growth rates, however, it is possible that FDI is a driving force of growth for specific industries or at the provincial level. As a result, a disaggregated analysis at the sectoral and provincial level can be fruitful in the study of the causal nexus between FDI and growth in China. In particular, if FDI is found to be a driver of income for some provinces, different incentives can be given to foreign
investors to attract a greater proportion of FDI to inland regions in order to reduce the income
gap between coastal and inland provinces. Second, it is possible that some of the previous
findings on the relation between FDI and GDP growth can be caused by over-rejection of the
null of no causality because of severe size distortions typical for small sample statistical
inference based on asymptotic theory. Consequently, there is also need for more individual
country studies because size distortions can be significantly lower when bootstrapping is used
and the meboot DGP is an excellent tool for performing such analyses using time series data.
Figure 2: Highest density confidence limits for the GDP equation, multivariate analysis, n=2.
Figure 3: Highest density confidence limits for the FDI equation, multivariate analysis, n=2.
References


