行政院國家科學委員會專題研究計畫 成果報告

型一誤差重要還是檢定力重要？條件動差檢定中的非單調檢定力問題

研究成果報告(精簡版)

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1 Introduction

Many applied researchers use statistical inference for different models in practice. An important issue in inferential methods for econometrics models is that some tests can exhibit nonmonotonic power (see, e.g., Nelson and Savin (1990), Vogelsang (1999), and Deng and Perron (2008)). That is, as the distance that alternative hypothesis deviates from the null grows, the power of the test actually decreases. The problem of nonmonotonic power is noted in a variety of tests such as tests in linear/nonlinear regression models of Hauck and Donner (1977), Bates and Watts (1988), and Nelson and Savin (1990), in the generalized method of moments (GMM) of Hall (2000) and Hall, Iuoue and Peixe (2003), and models with structural breaks in the mean of Andrews and Monahan (1992), Deng and Perron (2008), and Vogelsang (1999).

Applied researchers use consistent estimators for the variance covariance matrix when testing parameter restrictions on linear regressions such as the heteroskedasticity consistent covariance matrix estimators (HCCME) of White (1980) and the heteroskedasticity and autocorrelation consistent estimators (HACE) of Newey and West (1987). In the GMM literatures, Hall (2000) shows that the non-centered HACE in GMM method is not consistent when model is misspecified. Therefore, the overidentifying restriction test of GMM method base on the non-centered HACE may not be consistent under the alternative and exhibits nonmonotonic power in large sample. Hall (2000) considers a centered HACE and shows that the resulting overidentifying restriction test is consistent under both null and alternative; see also Hall and Inoue (2003), Chang (2005, 2007). However, Hall, Iuoue and Peixe (2003) shows that when the presence of neglected structural instability under the alternative, even the HACE is based on non-centered or centered autocovariances, the rate of increase of the overidentifying restrictions test is depending on the form of the instability.

Most Monte Carlo studies indicate that the main reason for nonmonotonic power is that in finite samples some nuisance parameters such as the variance estimator are poorly estimated under the (global) alternative; see Hall (2000), Crainiceanu and Vogelsang (2007), Juhl and Xiao (2009). Allen (2007) compares the powers of the overidentifying restriction tests using the centered and non-centered HACEs, but his Monte Carlo simulation shows that very little power is gain. MacKinnon and White (1985), Flachaire (2005), Godfrey (2006) and Godfrey and Orme (2004) propose several different forms of a variance-covariance matrix to control the finite sample significance levels. They find that hypothesis testings using the wild or jackknife bootstrap perform better in small samples. Goncalves and White (2005) show that tests based on the moving blocks bootstrap estimators have better finite samples performances. Recently, several authors impose a boundary condition for the HACE to restore the monotone power of tests; see Sul et al. (2005). Juhl and Xiao (2009) propose a modified variance estimator based on the nonparametrically demeaned data and show that the modified estimator diverges at a slower rate than the unmodified version; thus, tests based on the modified estimator retain their consistency under various diverging alternative hypotheses.

In many econometric and statistical applications, there often exist conditional moment (CM) restrictions that characterize the behavior of models of interest. For example, specifications for regression models and specifications for conditional probability models can be represented as CM restrictions. Once a model is specified, it is important to have specification tests on its validity. A CM test based on CM restrictions is a general framework that includes most model specification tests. For example, Newey (1985), Tauchen (1985), Wooldridge (1990), Bierens (1982, 1990), Bierens and Ploberger (1997), Bierens and Ginther (2001), Zheng (1998) to mention only a few. Although the nonmonotonic power problem have been studied in many testing literature, this problem is not discussed in the framework of CM tests. As Nelson and Savin (1990) pointed, "*While the existence of nonmonotonic power is not new, the surprising results are that this phenomenon occurs ... and it can be quite severe*". In this paper, the nonmonotonic power problem in the CM tests is investigated in finite samples by using Monte Carlo simulation. We show that the standard variance estimator used in the CM tests is consistent only under the null. Under the alternative, nonmonotonic power could arise from using an inconsistent estimate; CM tests can not retain their consistency under global alternatives. Therefore, the variance estimator is the main source of the nonmonotonic power problem in CM tests. Since the source of nonmonotonic power problem in CM test is the variance estimator, we suggest using the centered variance estimator in test with the aim of gaining power under global alternative. We examine the small sample performances of tests by Monte Carlo simulations. It is seen that the power functions of the tests are very sensitive to the behavior of the variance estimates.

2 Non-Centered Variance Estimators

Let y_t be a finite-dimensional vector of dependent variable(s) with index t, and $\mathcal{X}_t$ be the information set available in explaining y_t. Suppose that it is interested in estimating and testing a CM model of $y_t|\mathcal{X}_t$ with a $r \times 1$ vector of generalized residuals $m_t := m_t(y_t, x_t; \theta)$ for some finite $r \geq \dim(y_t)$, in which x_t denotes a vector of $\mathcal{X}_t$-measurable explanatory variables and $\theta \in \Theta \subset \mathbb{R}^p$ stands for a $p \times 1$ parameter vector. This CM model is defined to be correctly specified, if and only if, the martingale difference condition:

$$H_0 : \mathbb{E}[m_{ot}|\mathcal{X}_t] = 0,\ m_{ot} := m_t|_{\theta=\theta_0},$$

is satisfied for some unique $\theta_o \in \Theta$. Let z_t be a $q \times r$ matrix of $\mathcal{X}_t$-measurable misspecification indicators, the $q \times 1$ testing function: $z_t m_t$ must satisfy the martingale-difference condition:

$$\mathbb{E}[z_t m_{ot}|\mathcal{X}_t] = z_t \mathbb{E}[m_{ot}|\mathcal{X}_t] = 0,$$

which further implies the unconditional moment restriction: $\mathbb{E}[z_t m_{ot}] = 0$. The CM test checks this restriction by examining whether the estimated moment: $T^{-1}\sum_{t=1}^{T} z_t \hat{m}_t$ is significantly different from zero, in which $\hat{m}_t := m_t|_{\theta=\hat{\theta}_T}$ with $\hat{\theta}_T$ representing estimator of θ_o.

Let u_t be the error term of the specified regression model. Suppose that the CM test is based on an estimator of θ_o which is solved from the estimating equation: $T^{-1}\sum_{t=1}^{T} x_t \hat{u}_t = 0$, from some $p \times 1$ estimating function that does not contain the same components of the testing function $z_t \hat{m}_t$, $x_t' = -\nabla_\theta u_t$ is $\mathcal{X}$-measurable function and $\hat{u}_t := u_t|_{\theta=\hat{\theta}_T}$. The estimator $\hat{\theta}_T$ has the following representation:

$$\begin{aligned}\sqrt{T}(\hat{\theta}_T - \theta_o) &= -\left[\frac{1}{T}\sum_{t=1}^{T} x_t \nabla_\theta u_t\right]^{-1} \frac{1}{\sqrt{T}}\sum_{t=1}^{T} x_t u_t + o_p(1) \\ &= \mathbb{E}(x_t x_t')^{-1} \frac{1}{\sqrt{T}}\sum_{t=1}^{T} x_t u_t + o_p(1)\end{aligned}$$

If $m_t = u_t$, then $\nabla_\theta m_t = \nabla_\theta u_t = -x_t'$.

$$\begin{aligned}\frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t \hat{m}_t &= \frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t m_t + \left(\frac{1}{T}\sum_{t=1}^{T} z_t \nabla_\theta m_t\right)\sqrt{T}(\hat{\theta}_T - \theta_o) + o_p(1) \\ &= \frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t m_t - \mathbb{E}(z_t x_t')\,\mathbb{E}(x_t x_t')^{-1}\frac{1}{\sqrt{T}}\sum_{t=1}^{T} x_t u_t + o_p(1) \\ &= \frac{1}{\sqrt{T}}\sum_{t=1}^{T}[z_t - \mathbb{E}(z_t x_t')\,\mathbb{E}(x_t x_t')^{-1} x_t] u_t + o_p(1).\end{aligned}$$

Let $z_t^* := z_t - \mathbb{E}(z_t x_t')\,\mathbb{E}(x_t x_t')^{-1} x_t$, we can rewrite the above equation as follows:

$$\frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t \hat{u}_t = \frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t^* u_t + o_p(1).$$

When model is correctly specified or say under the null hypothesis, one has $\mathbb{E}(u_t|\mathcal{X}_t) = 0$, and the test statistic converges to a normal distribution by central limit theorem under suitable regularity conditions:

$$\frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t \hat{u}_t \xrightarrow{d} N(0, V),$$

where the asymptotic variance $V := \mathbb{E}[z_t^* u_t u_t' z_t^{*\prime}]$ is a $q \times q$ variance covariance matrix. Follow Hall's (2000) suggestion, the non-centered and centered variance estimators are considered. The non-centered variance estimator is specified as:

$$\hat{\Sigma}_T^u := \frac{1}{T}\sum_{t=1}^{T}(z_t^* \hat{u}_t)(z_t^* \hat{u}_t)',$$

and a centered variance estimator of the variance

$$\hat{\Sigma}_T^c := \frac{1}{T}\sum_{t=1}^{T}\left(z_t^* \hat{u}_t - \frac{1}{T}\sum_{t=1}^{T} z_t^* \hat{u}_t\right)\left(z_t^* \hat{u}_t - \frac{1}{T}\sum_{t=1}^{T} z_t^* \hat{u}_t\right)'.$$

Considering two test statistics for testing CM restrictions, I first define the statistic with normalizing centered variance estimator as

$$M_T^u := \left[\frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t \hat{u}_t\right]'(\hat{\Sigma}_T^u)^{-1}\left[\frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t \hat{u}_t\right],$$

and define the statistic with non-centered variance estimator as

$$M_T^c := \left[\frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t\hat{u}_t\right]' (\hat{\Sigma}_T^c)^{-1}\left[\frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t\hat{u}_t\right].$$

Under H_0, both variance estimators converge to the asymptotic variance V, and it is derived that $M_T^u \xrightarrow{d} \chi^2(q)$ and $M_T^c \xrightarrow{d} \chi^2(q)$, where $\chi^2(q)$ the chi-square distribution with q degrees of freedom. This result demonstrates that "centering" in constructing normalizing matrices leads to correct size and does not affect the asymptotic behavior when model is correctly specified.

If the model is incorrectly specified, the limiting distribution of the statistic is different from that under correctly specified model. In the following, I consider two types of alternatives; one is a global alternative and the other is the local alternative. Consider a general alternative hypothesis:

$$H_1 : \mathbb{E}[u_t|\mathcal{X}_t] = w_t'\delta.$$

This test is expected to be powerful against H_1 because the conditional expectation of z_tu_t becomes $\mathbb{E}[z_tu_t|\mathcal{X}_t] = z_tw_t'\delta$ under H_1, which implies that $\mathbb{E}[z_tu_t] = \mathbb{E}[z_tw_t']\delta$ is a $q \times 1$ nonzero vector provided that $\mathbb{E}[z_tw_t']$ is positive definite. The asymptotic behavior of M_T^c or M_T^u depends on two terms: one is the asymptotic behavior of $T^{-1/2}\sum_{t=1}^{T} z_t\hat{u}_t$ and the other is the asymptotic behavior of $\hat{\Sigma}_T^u$ and $\hat{\Sigma}_T^c$. Because

$$\frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t\hat{u}_t = \frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t^*(u_t - w_t'\delta) + \frac{1}{\sqrt{T}}\sum_{t=1}^{T} z_t^*w_t'\delta + o_p(1),$$

under H_1 the first term on the right-hand-side of the above equation converges to distribution $N(0, \mathbb{E}[z_t^*u_tu_t'z_t^{*\prime}])$ which is $O_p(1)$, and the asymptotics of $T^{-1/2}\sum_{t=1}^{T} z_t\hat{u}_t$ depends on the second term $T^{-1/2}\sum_{t=1}^{T} z_t^*w_t'\delta$. In addition, under H_1, the centered variance estimator $\hat{\Sigma}_T^c \xrightarrow{p} V$ and the non-centered variance estimator

$$\hat{\Sigma}_T^u \xrightarrow{p} V + \mathbb{E}(z_tw_t')\delta\delta'\mathbb{E}(w_tz_t'),$$

which follows from

$$\frac{1}{T}\sum_{t=1}^{T} z_t\hat{u}_t = \mathbb{E}(z_tw_t')\delta + o_p(1).$$

The limits of $\hat{\Sigma}_T^c$ and $\hat{\Sigma}_T^u$ differ by an extra term: $\mathbb{E}(z_tw_t')\delta\delta'\mathbb{E}(w_tz_t')$. When $T \to \infty$, M_T^c diverges but the asymptotic distribution of M_T^u is unknown by the extra term.

The power of the test based on M_T^c approaches 1 but the power of M_T^u is unknown depending on the functional form of the alternative hypothesis and the additional term $\mathbb{E}(z_t w_t')\delta\delta'\mathbb{E}(w_t z_t')$. This is the first finding of this paper that the CM test based on uncentered variance may constitute nonmonotonic power.

Consider one special case that $\mathbb{E}(z_t w_t')\delta = O(1)$ such as a constant function, then M_T^u diverges and the power of M_T^u approaches 1. The other special case is the local alternatives:

$$H_1^A : \mathbb{E}[u_t|\mathcal{X}_t] = \gamma/\sqrt{T}.$$

This local alternative is approaching to the null when T goes to infinity. Under H_1^A, both $\hat{\Sigma}_T^c \xrightarrow{p} V$ and $\hat{\Sigma}_T^u \xrightarrow{p} V$. Therefore, under H_1^A, when $T \to \infty$, both statistics M_T^c and M_T^u diverge and the power of the tests approach 1. Note that in these cases, although the asymptotic power of M_T^u and M_T^c approach 1 and both CM test are consistent, it is found that when T is small, the finite sample power of M_T^u and M_T^c are different. It is argued that the divergence rate of M_T^u is slower than that of M_T^c. Therefore, in practice, when the sample size is not large, the finite sample power of M_T^u is smaller than that of M_T^c. This is the motivation of this paper which focuses on the finite sample comparison of two CM tests.

3 Monte Carlo Simulation

In this section, three Monte Carlo experiments to examine the effectiveness of the proposed tests are conducted. In particular, we compare the powers of M_T^u and M_T^c in sample mean and conditional mean examples. All examples consider sample sizes of $T = 10, 20, 50$, the nominal size is 5%, and the number of replication is 2000.

3.1 Sample Mean Example

For the following two hypotheses,

$$H_0 : x_t \sim N(0, \sigma_0^2), \quad H_1 : x_t \sim N(\mu, \sigma_0^2), \tag{1}$$

then $z_t \hat{u}_t = x_t$, $\hat{\Sigma}_T^u := (\hat{\sigma}_T^u)^2 = T^{-1}\sum_{t=1}^T x_t^2$, $\hat{\Sigma}_T^c := (\hat{\sigma}_T^c)^2 = T^{-1}\sum_{t=1}^T (x_t - \bar{x})^2$, with $\bar{x} = \sum_{t=1}^T x_t/T$. In the sample mean example, we consider cases with $\sigma_0^2 = 1, 2, 4$. The rejection rates of sample mean example are presented in Figure 1. In the figure, the horizontal axis is μ which represents the deviation from the null, the vertical axis is the rejection rate of tests, the dashed line represents the rejection rate of M_T^u and the solid line shows those of M_T^c. From Figure 1, we can find that when the sample size is small, the finite sample power of M_T^c is higher than that of M_T^u; the difference between the powers becomes smaller as the sample size gets larger. In addition, for fixed sample size T, the difference between powers of M_T^c and M_T^u are smaller for $\sigma_0^2 = 1$ and are larger when $\sigma_0^2 = 4$.

3.2 Conditional Mean Example

$$\begin{aligned} H_o &: \ y_t = x_t'\beta + u_t, \quad u_t|\mathcal{X}_{t-1} \sim N(0, \sigma_{1t}^2); \\ H_1 &: \ y_t = x_t'\beta + u_t, \quad u_t|\mathcal{X}_{t-1} \sim N(w_t'\delta, \sigma_{2t}^2), \end{aligned} \tag{2}$$

with β a $k \times 1$ vector of parameters. The CM restriction is $\mathbb{E}(u_t|\mathcal{X}_{t-1}) = 0$. Suppose that x_t is independent and identically distributed $N(0, 1)$. The conditional mean example is also considered with $w_t'\delta = \mu$, $\sigma_{1t}^2 = \sigma_{2t}^2 = 1, 2, 4$. In this example, let $\hat{\beta}$ be the least square estimator, $\hat{u}_t = y_t - x_t'\hat{\beta}$, $z_t\hat{u}_t = x_t\hat{u}_t$, $\hat{\Sigma}_T^u := T^{-1}\sum_{t=1}^T x_t\hat{u}_t^2 x_t'$,

$$\hat{\Sigma}_T^c := \frac{1}{T}\sum_{t=1}^T \left[x_t\hat{u}_t - \frac{1}{T}\sum_{t=1}^T x_t\hat{u}_t\right]\left[x_t\hat{u}_t - \frac{1}{T}\sum_{t=1}^T x_t\hat{u}_t\right]'.$$

The rejection rates of conditional mean example is presented in Figure 2. In the figure, the horizontal axis is μ which represents the deviation from the null, the vertical axis is the rejection rate of tests, the dashed line represents the rejection rate of M_T^u and the solid line shows those of M_T^c. From Figure 2, we can find that when the sample size is small, the finite sample power of M_T^c is much higher than that of M_T^u; the difference between the powers becomes smaller as the sample size gets larger. In addition, for fixed sample size T, the difference between powers of M_T^c and M_T^u are smaller for $\sigma_0^2 = 1$ and are larger when $\sigma_0^2 = 4$.

4 Conclusions

In this paper, a modified CM test with centered variance estimator is proposed. The nonmonotonic power problem can be alleviated with considering the modified CM test. Our Monte Carlo simulation shows that the CM test based on centered variance has lower finite sample powers, while the CM test based non-centered variance has higher finite sample powers.

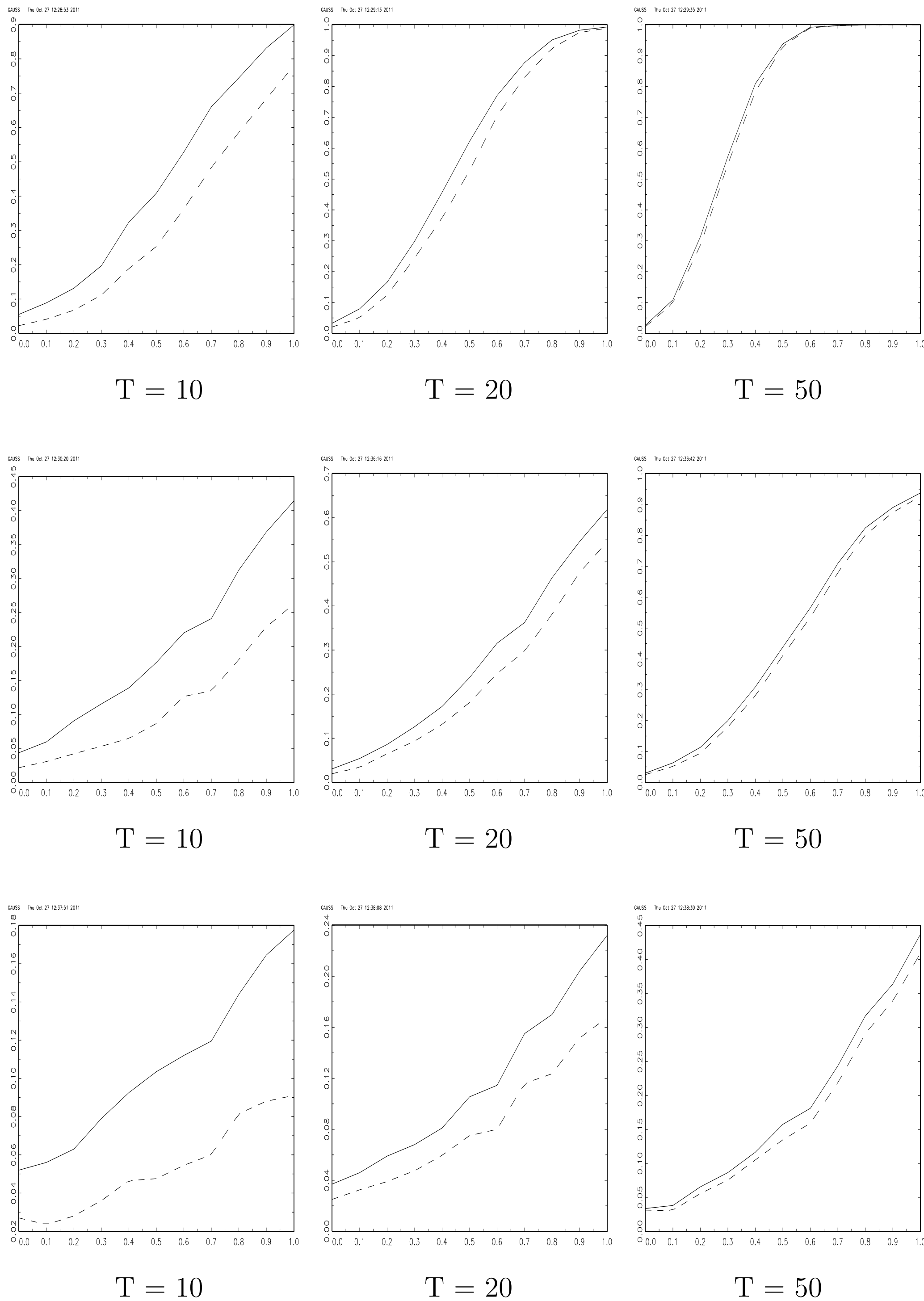

Figure 1: Finite Sample Powers in Sample Mean Examples with $\sigma_0^2 = 1$ for upper panel, $\sigma_0^2 = 2$ for middle panel, $\sigma_0^2 = 4$ for lower panel.

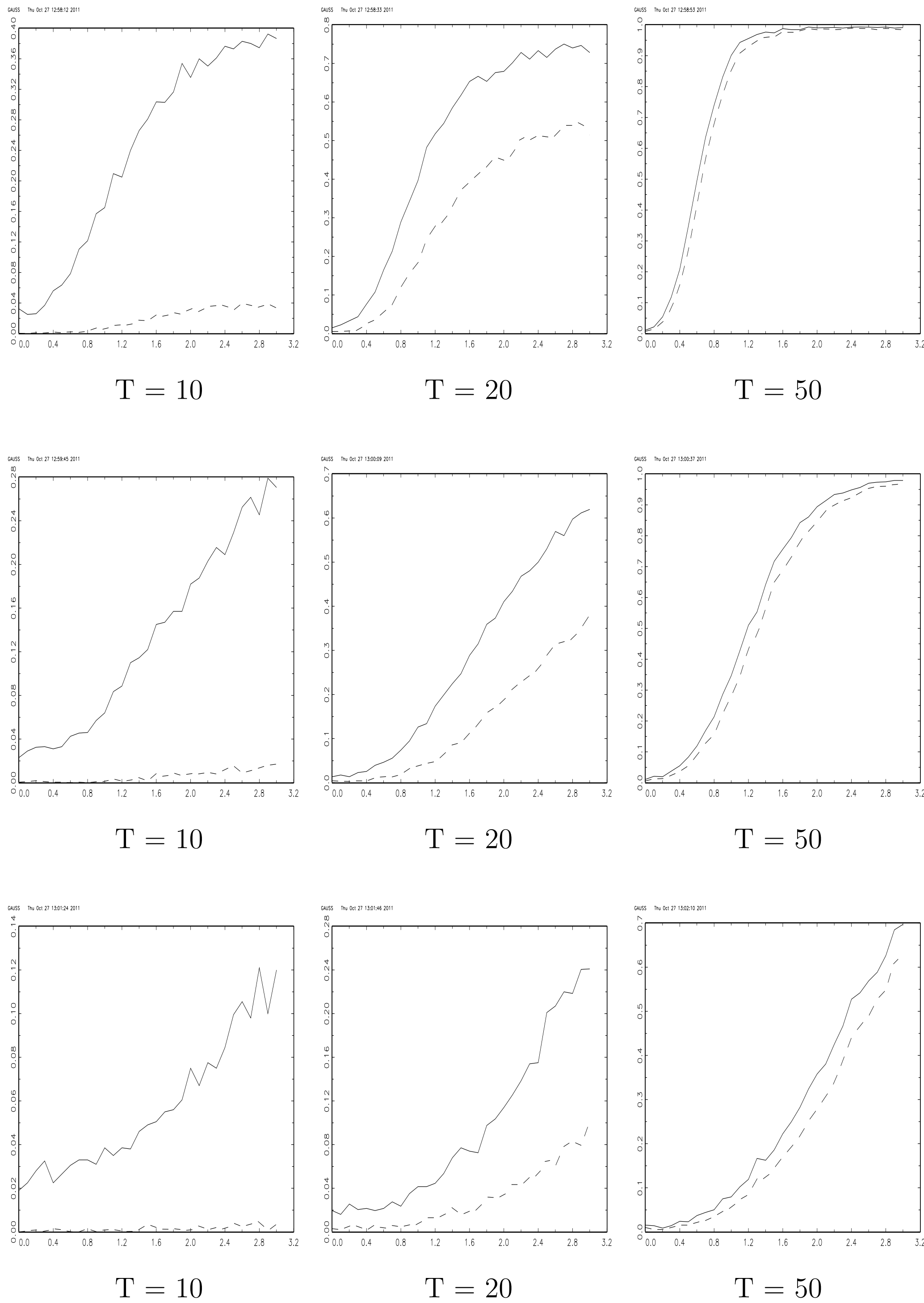

Figure 2: Finite Sample Powers in Conditional Mean Examples with $\sigma_0^2 = 1$ for upper panel, $\sigma_0^2 = 2$ for middle panel, $\sigma_0^2 = 4$ for lower panel.

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國科會補助計畫衍生研發成果推廣資料表

日期:2011/10/28

國科會補助計畫	計畫名稱: 型一誤差重要還是檢定力重要?條件動差檢定中的非單調檢定力問題
	計畫主持人: 林馨怡
	計畫編號: 99-2410-H-004-057- 學門領域: 數理與數量方法

無研發成果推廣資料

99 年度專題研究計畫研究成果彙整表

計畫主持人：林馨怡	計畫編號：99-2410-H-004-057-
計畫名稱：型一誤差重要還是檢定力重要？條件動差檢定中的非單調檢定力問題	

成果項目			量化：實際已達成數（被接受或已發表）	量化：預期總達成數(含實際已達成數)	量化：本計畫實際貢獻百分比	單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
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		研究報告/技術報告	1	1	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	0	0	100%	人次	
		博士生	0	2	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	0	1	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	無

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

   ■達成目標

   □未達成目標（請說明，以 100 字為限）

   □實驗失敗

   □因故實驗中斷

   □其他原因

   說明：

2. 研究成果在學術期刊發表或申請專利等情形：

   論文：□已發表 ■未發表之文稿 □撰寫中 □無

   專利：□已獲得 □申請中 ■無

   技轉：□已技轉 □洽談中 ■無

   其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）