Estimating the Persistence and the Autocorrelation Function of a Time Series that is Measured with Error*

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Abstract

An economic time series can often be viewed as a noisy proxy for an underlying economic variable. Measurement errors will influence the dynamic properties of the observed process and may conceal the persistence of the underlying time series. In this paper we develop instrumental variable (IV) methods for extracting information about the latent process. Our framework can be used to estimate the autocorrelation function of the latent volatility process and a key persistence parameter. Our analysis is motivated by the recent literature on realized (volatility) measures, such as the realized variance, that are imperfect estimates of actual volatility. In an empirical analysis using realized measures for the DJIA stocks we find the underlying volatility to be near unit root in all cases. Although standard unit root tests are asymptotically justified, we find them to be misleading in our application despite the large sample. Unit root tests based on the IV estimator have better finite sample properties in this context.

Keywords: Persistence, Autocorrelation Function, Measurement Error, Instrumental Variables, Realized Variance, Realized Kernel, Volatility.

JEL Classification: C10; C22; C80.

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1. Introduction

Many economic time series are constructed from survey statistics or composed of estimates that involve sampling error. It is therefore natural to view such time series as proxies for the underlying population quantities.

To take a concrete example, consider a daily time series of realized variances. Each element of this time series can be viewed as a noisy estimate of the latent volatility. Much progress has recently been made in estimating financial volatility from high-frequency data using realized measures, such as the realized variance. Despite this progress, it is important to discriminate between the realized measure of volatility and the underlying population quantity. Even with the most accurate estimators of daily volatility, which can utilize thousands of high-frequency prices, the standard error for a single estimate is rarely less than 10% of the point estimate, see e.g. Barndorff-Nielsen, Hansen, Lunde & Shephard (2008*a*). Measurement errors of this magnitude cause the autocorrelation function of the observed time series to look distinctively different from that of the underlying time series.

In this paper, we develop instrumental variable methods that facilitate the analysis of the latent time series. The instrumental variables are lagged value of the observed time series, and we have in mind a situation where the latent process is persistent, because non-zero autocorrelations are needed for these instruments to be valid. In fact, the more persistent is the latent time series the "stronger" will these instruments be, other things being equal. We focus on two aspects of the problem. First, we show that the IV methods provide an effective way to assess the degree of persistence for the latent time series. An implication is that unit root tests based on IV regression methods have better finite sample properties than conventional tests. Second, we propose an alternative estimator of the autocorrelation function (ACF) for the latent time series. This estimator is more informative about the ACF of the latent process, in particular when the latter is a persistent process.

Our basic framework is simple: We model the latent time series as an ARMA(p,q) process and the measurement error as a white noise process. The empirical problem that has motivated this analysis is the situation where the latent time series is daily volatility whereas the observed time series is a sequence of realized measure, such as the realized variance, that are compute with high frequency data. Because each of these estimates are computed with different high frequency data (data from distinct days) it is reasonable to assume that their sampling errors are uncorrelated.

The analysis that we present in this paper is related to the literature on unit root test in the context of moving average innovations. The unit root test based on instrumental variables (that is very similar to ours) was proposed by Hall (1989), and Perron & Ng (1996) have proposed another unit root test that is also robust to the sort of moving average innovations that

arises in this context. Our analysis is also related to the literature on unobserved component models that deals with signal extraction, detrending and filtering of noisy time series (see for example Ashley & Vaughan (1986), Watson (1986), Harvey (2001), Harvey & Proietti (2005) and Harvey & De Rossi (2006)). In this strand of the literature the statistical treatment of the underlying component is usually carried out by setting up the state space form and applying the associated (Kalman) filter and smoothing algorithms. These methods have been applied to realized measures of volatility by Barndorff-Nielsen & Shephard (2002), Barndorff-Nielsen, Nielsen, Shephard & Ysusi (2004), Hansen & Lunde (2005*b*) and Koopman, Jungbacker & Hol (2005). These papers show that the measurement error (sampling error) is nontrivial component of the realized variance.

Our analysis contributes with new theoretical results that helps to identify the dynamic properties of the latent process of interest. Specifically in relation to the persistence of the underlying process. The IV methods we develop in this paper compliments existing methods and offers some advantages. For instance, the IV-based autocorrelation function shares the simplicity and non-parametric nature of the conventional empirical autocorrelation.

We make the following contributions: First, we propose simple instrumental variable estimators of a key parameter that captures the persistence of autoregressive moving average (ARMA) processes. For an AR(1) process the persistence parameter is simply the autoregressive coefficient. The persistence parameter can be estimated with simple IV estimators, and for the ARMA(1,1) case we derive the optimal IV estimator that exploits the particular covariance structure in this framework. Second, we propose an approximate autocorrelation function for the latent time series. This is important because many economic time series can be viewed as noisy proxies of the fundamental underlying process, and measurement errors can cause the ACF of the observed time series to look distinctively different from that of the latent process. Third, in our empirical analysis of realized measures of volatility, we find that actual volatility is very close to having a unit root. In fact the largest autoregressive root is typically in the range between 0.98 and 1.00. In this context, we show that standard unit root tests can be very misleading. Standard unit root tests can be asymptotically justified in this context, but their finite sample properties are quite poor – even with a sample size that is well over a thousand observations. The main reason being that the measurement errors are relatively large in these time series. Fourth, we make some remarks on fractionally integrated processes. The popularity of fractionally integrated processes for the modeling of volatility is to some extend driven by two empirical observations: 1) The shape of the ACF for observed volatility; and 2) The apparent rejection of the unit root hypothesis using conventional unit root tests. In this paper we argue that neither can be taken as evidence of fractional integration. The reason is that a unit root process, or a local-to-unit root process, can also induce these empir-

ical observations, provide a sufficient layer of measurement errors, a result that resembles the aggregation result by Granger (1980). The measurement error is so pronounced in these time series that it ought to be accounted for. However we do not dismiss the fractionally integrated model as a good model of volatility. The reason is that our approximate ACF does have features that are consistent with long memory processes and the instrumental variable unit root tests do reject the unit root hypothesis for most of the volatility time series. So in this regard we arrive at the same conclusion as Wright (1999) who based his analysis on squared daily returns. Wright (1999) tested the unit root hypothesis using the test by Perron & Ng (1996).

This paper is organized as follows. In Section 2, we describe the theoretical framework, introduce the instrumental variable estimator and derive its asymptotic properties. In Section 3 we introduce a novel estimator of the autocorrelation function for the latent time series and illustrate some of its advantages. In Section 4 we present an empirical analysis with realized measures of volatility, two macroeconomic time series of inflation, and two long time series of absolute returns. We estimate the ACF for the underlying time series for all time series. For the time series of realized measures we show that the underlying volatility is highly persistent and close to unit root in all cases. Concluding remarks are given in Section 4. Appendix A contains proofs of all Theorems and Lemmas that are stated in the main body of the paper, and Appendix B presents additional empirical results.

2. An Instrumental Variable Approach to Assessing the Persistence of a Latent Time Series

In this section we study some methods for assessing the persistence of a time series that is measured with error. We consider a class of simple instrumental variable estimators, and show that these are consistent for the parameter that measures the persistence.

We use an ARMA(p,q) specification for the latent time series, y_t, and treat the observed volatility, x_t, as a noisy and possibly biased estimate of $y_{t.}$. So our model is

$$\varphi(L)(y_t - \delta) = \theta(L)\varepsilon_t, \tag{1}$$

$$x_t = y_t + \xi + \eta_t. \tag{2}$$

In the context of time series of volatility, one may take the latent time series to be the integrated variance on day t, $\text{IV}_t = \int_{t-1}^{t} \sigma_s^2 \text{d}s$, and the observed time series to be the realized variance for day t, RV_t. In our empirical analysis we study two types of realized measures, specifically the realized variance and the realized kernel.

The model has the following implication for the observed time series.

Lemma 1 *Given (1) and (2) we have*

$$\varphi(L)\left(x_t - \delta - \xi\right) = \theta(L)\varepsilon_t + \varphi(L)\eta_t. \tag{3}$$

The Lemma shows that x_t is an ARMA process with the exact same autoregressive polynomial. In the context of time series of volatility this result was noted in Barndorff-Nielsen & Shephard (2002) and Meddahi (2003), see also Andersen, Bollerslev & Meddahi (2004).

We make the following assumptions.

Assumption 1 *The characteristic polynomials,*

$$\varphi(z) = 1 - \varphi_1 z - \cdots - \varphi_p z^p \qquad \textit{and} \qquad \theta(z) = 1 - \theta_1 z - \cdots - \theta_q z^q,$$

do not have any roots in common and are such that

$$\varphi(z)/\left(1 - z\right) = 0 \;\Rightarrow\; |z| > 1 \qquad \textit{and} \qquad \theta(1) \neq 0,$$

and $\{\varepsilon_t, \eta_t\}$ *is a sequence of independent and identically distributed random variables with zero mean and* $\sigma_\varepsilon^2 = \mathrm{var}(\varepsilon_t)$, $\sigma_\eta^2 = \mathrm{var}(\eta_t)$, *and* $\mathrm{cov}(\varepsilon_t, \eta_t) = 0$.

With Assumption 1 we ensure that y_t is either integrated of order zero, I(0), or integrated of order one I(1). The first part of the Assumption allows $\varphi(z)$ to have a single unit root, $\varphi(1) = 0$, but the multiplicity of this unit root is at most one. This rules out integration of an order higher than one. For example y_t is I(2) when the multiplicity of the unit root is two. The requirement that $\theta(1) \neq 0$ ensures that $\theta(L)\varepsilon_t$ is I(0). Without this condition we would not have the previous relation between the roots of $\varphi(z)$ and the order of integration.

A key parameter for our analysis is the *persistence parameter* that is defined by

$$\pi = \max_{i=1,\ldots,p} \frac{1}{|z_i^*|},$$

where $z_1^*, \ldots, z_p^*$ are the roots of the characteristic polynomial, i.e. $\varphi(z_i^*) = 0$, $i = 1, \ldots, p$. We note that $\pi = 1$ when $\varphi(z)$ has a unit root and for persistent processes we have

$$\pi \approx \varphi_\bullet = \varphi_1 + \cdots + \varphi_p,$$

(e.g. when $p = 1$ we have $\pi = \varphi_\bullet = \varphi_1$). This motivates the terminology "persistence parameter".

The persistence parameter can also be defined from the companion form for y_t. Without loss of generality consider the case with $\delta = 0$ and $\theta(z) = 1$. Then $Y_t = (y_t, \ldots, y_{t-p+1})'$, can

be expresses as a VAR(1) process, $Y_t = \Phi Y_{t-1} + \varepsilon_t^*$, where $\varepsilon_t^* = (\varepsilon_t, 0, \ldots, 0)'$, and

$$\Phi = \begin{pmatrix} \varphi_1 & \varphi_2 & \cdots & \varphi_{p-1} & \varphi_p \\ 1 & 0 & \cdots & & 0 \\ 0 & 1 & \cdots & & \\ \vdots & & \ddots & & \\ 0 & & & 1 & 0 \end{pmatrix}.$$

The persistence parameter, π, is simply given as the spectral radius of Φ (the largest eigenvalue as measured in absolute value).

Much of our analysis can be understood from the simplest case where $p = 1$ and $q = 0$. This case is outlined in the following example.

Example 1 *Suppose that Assumption 1 holds with $p = 1$ and $q = 0$. Then y_t is an AR(1) process and by manipulating the two expressions,*

$$y_t = \pi y_{t-1} + (1 - \pi)\delta + \varepsilon_t \qquad \text{and} \qquad x_t = y_t + \xi + \eta_t,$$

we have that $x_t = \pi x_{t-1} + (1 - \pi)(\delta + \xi) + \varepsilon_t + \eta_t - \pi\eta_{t-1}$.

Note that we have parameterized the constant in a way that it vanishes whenever $\pi = 1$. This ensures that y_t does not have a deterministic trend in the unit root case.

2.1. **Instrumental Variable Estimators**

We consider the class instrumental variable estimators of the persistence parameter π, that we defined in (3). These estimators have the form

$$\hat{\pi}_{\text{IV}_z} = \frac{\sum_{t=1}^n z_t x_{t+1}}{\sum_{t=1}^n z_t x_t}, \tag{4}$$

where we refer to z_t as an instrumental variable or simply an instrument. The expression (4) defines a large class of estimators that includes the least squares estimator and instrumental variable estimators including the two-stage least squares estimator. For example, when the instrumental variable is a lagged value of the observed time series (less its sample average), we have

$$\hat{\pi}_{\text{IV}_j} = \frac{\sum_{t=1}^n (x_{t-j} - \bar{x}_j) x_{t+1}}{\sum_{t=1}^n (x_{t-j} - \bar{x}_j) x_t}, \qquad j = 0, 1, 2, \ldots.$$

where $\bar{x}_j = n^{-1} \sum_{t=1}^n x_{t-j}$. When $j = 0$ this estimator simplifies to the least squares estimator

$$\hat{\pi}_{\text{LS}} = \frac{\sum_{t=1}^n (x_t - \bar{x}_0) x_{t+1}}{\sum_{t=1}^n (x_t - \bar{x}_0) x_t}.$$

The two-stage least squares (TSLS) estimator, which is based on multiple instruments, $\tilde{Z}_t = (x_{t-J_1} - \bar{x}_{J_1}, \ldots, x_{t-J_2} - \bar{x}_{J_2})'$ with $0 \leq J_1 \leq J_2$, can also be expressed in the form of (4). In this case we have

$$z_t = \tilde{Z}_t' \hat{\alpha}_{\text{TSLS}}, \qquad \text{where} \quad \hat{\alpha}_{\text{TSLS}} = \left(\sum_{t=1}^{n} \tilde{Z}_t \tilde{Z}_t' \right)^{-1} \sum_{t=1}^{n} \tilde{Z}_t x_t. \tag{5}$$

This is not surprising, because the first step in a TSLS procedure amount to a dimension reduction, where a vector of instruments is mapped into a vector of instruments that has a dimension that matches that of the regression parameters. The present problem has a particular covariance structure that we can utilize to determine the optimal linear combination, α^*, of the set of instrumental variables. This will lead to an IV estimator that is more efficient than the TSLS estimator.

2.2. **Properties of Estimators: The AR(1) Case**

Initially we establish the properties of our estimators assuming that y_t is a simple AR(1) process. Later we consider more general ARMA specifications, and evaluate the extent to which the IV estimators are robust.

Lemma 2 *Suppose that Assumption 1 holds with $p = 1$ and $q = 0$, so that $\pi = \varphi_1$. When $|\pi| < 1$ and y_0 is assigned the stationary distribution for y_t, we have*

$$\text{var}(y_t) = \sigma_y^2 = \frac{\sigma_\varepsilon^2}{1 - \pi^2} \quad \textit{and} \quad \text{cov}(x_t, x_{t-h}) = \begin{cases} \sigma_y^2 + \sigma_\eta^2 & \textit{for } h = 0, \\ \pi^h \sigma_y^2 & \textit{for } h \neq 0. \end{cases}$$

When $|\pi| < 1$ we have the usual errors-in-variable problem, because x_{t-1} and $u_t = \varphi(L)\eta_t + \theta(L)\varepsilon_t$ are correlated. For instance, under the assumptions of Lemma 2 we have $u_t = \eta_t - \pi\eta_{t-1} + \varepsilon_t$, so that $\text{cov}(x_{t-1}, u_t) = -\pi\sigma_\eta^2$. This correlation causes the well known attenuation bias of the least squares estimator, which has previously been discussed in the context of realized measures by Barndorff-Nielsen & Shephard (2002).

Theorem 1 (least squares estimator) *Suppose that Assumption 1 holds with $p = 1$ and $q = 0$. Let $\lambda = \sigma_\eta^2 / \sigma_\varepsilon^2$.*
(i) We have

$$\hat{\pi}_{\text{LS}} \xrightarrow{p} \pi \frac{1}{1 + \lambda(1 - \pi^2)}.$$

(ii) When $\pi = 1$ we have

$$n(\hat{\pi}_{\text{LS}} - 1) \xrightarrow{d} \frac{\int_0^1 (W_u - \bar{W}) \mathrm{d}W_u - \lambda}{\int_0^1 (W_u - \bar{W})^2 \mathrm{d}u}.$$

The first part of Theorem 1 shows that the least squares estimator is inconsistent unless $\lambda = 0$ or $\pi = 1$. Although measurement errors, $\lambda > 0$, do not render the least squares estimator inconsistent when $\pi = 1$, it does affect the asymptotic distribution, because λ shows up in the limit distribution. Despite the consistency of $\hat{\pi}_{\text{LS}}$ in the unit root case, the stochastic bias,

$$-\frac{\lambda}{n\int_0^1 (W_u - \bar{W})^2 \mathrm{d}u}, \tag{6}$$

need not be negligible in finite samples. This will be illustrated in our empirical application, where the bias is sizable despite a large sample size.

When $p = 1$ such that $\varphi(L) = 1 - \pi L$, we have the following decomposition of our estimators,

$$\hat{\pi}_{\text{IV}_z} = \pi + \frac{\sum_{t=1}^n z_t u_{t+1}}{\sum_{t=1}^n z_t x_t}, \qquad \text{where} \quad u_{t+1} = \varepsilon_{t+1} + \eta_{t+1} - \pi\eta_t.$$

This shows the key to consistency whenever $|\pi| < 1$ is an instrument that is uncorrelated with u_{t+1}. For example, when $y_t \sim$ARMA(1,1) as in Meddahi (2002, 2003), the instrument $z_t = x_{t-j} - \bar{x}_j$ is valid for any $j \geq 1$, because $\text{cov}(x_{t-j}, u_{t+1}) = 0$ for $j \geq 1$.

Theorem 2 (instrumental variable estimator) *Suppose that Assumption 1 holds with* $p = 1$ *and* $q = 0$.
(i) *When* $|\pi| < 1$ *we have for* $j > 0$

$$n^{1/2}(\hat{\pi}_{\text{IV}_j} - \pi) \xrightarrow{d} N\left[0, \pi^{-2j}\left(1-\pi^2\right)\left\{1 + 2\left(1-\pi^2\right)\lambda + \left(1-\pi^4\right)\lambda^2\right\}\right],$$

where $\lambda = \sigma_\eta^2/\sigma_\varepsilon^2$.
(ii) *(Hall, 1989) When* $\pi = 1$ *we have for* $j > 0$

$$n(\hat{\pi}_{\text{IV}_j} - \pi) \xrightarrow{d} \frac{\int_0^1 (W_u - \bar{W})\mathrm{d}W_u}{\int_0^1 (W_u - \bar{W})^2 \mathrm{d}u}.$$

For the case where $y_t \sim$AR(1), Theorem 2 shows that the instrumental variable estimator is consistent for π, when $j \geq 1$. The first part of the Theorem shows that x_{t-1} is the most efficient instrument variables, amongst $x_{t-1}, x_{t-2}, \ldots$, when $|\pi| < 1$, because $\hat{\pi}_{\text{IV}_1}$ has the smallest asymptotic variance. This is intuitive because the autocovariance function is for $j \geq 1$ given by $\text{corr}(x_t, x_{t-j}) = \pi^j$, so that x_{t-1} is more correlated with x_t than is x_{t-j}, for $j \geq 2$. The asymptotic distribution for the case where $\pi = 1$ is due to Hall (1989), who emphasized the benefits of using $\hat{\pi}_{\text{IV}_j}$ to test for unit roots rather than $\hat{\pi}_{\text{LS}}$, because the former has an asymptotic distribution that is free of the nuisance parameter, $\lambda = \sigma_\eta^2/\sigma_\varepsilon^2$. c.f. Theorem 1 (ii) and Theorem 2 (ii).

Having an asymptotic distribution that depends on nuisance parameters is obviously inconvenient, but the conventional unit root test has another flaw that is more serious. The

standard OLS-based unit root test is known to be highly size distorted in the presence of a large moving average root, see Schwert (1989) and Perron & Ng (1996). This size distortion is largely due to the stochastic bias that we defined in (6). Despite the fact that the stochastic bias is only of order $O_p(n^{-1})$, which suggests it vanishes quickly as $n \to \infty$, it can play a major role even if n is large. The reason is that λ can be large, as is the case in our application with realized measures, so that the bias still plays a major role. This is indeed the case in our application with realized measures of volatility where n is close to 2,000. For the time series of realized variances we find the least squares estimator to be about 30% smaller than the instrumental variable estimator, and for the more accurate estimator of volatility, the realized kernel, we find the downward bias to be about 15%.

The instruments in Theorem 2 are single variable instruments, in the sense that they are based on a single lag of x_t. When $|\pi| < 1$ we can construct a more efficient instrumental variable by taking a linear combination of multiple instruments, $(x_{t-1}, x_{t-2}, \ldots)$.

Theorem 3 (optimal instrument) *Suppose that Assumption 1 holds with $p = 1$ and $q = 0$ and consider the case where $|\pi| < 1$. Let $Z_t = (x_{t-1} - \bar{x}_1, \ldots x_{t-J} - \bar{x}_J)'$, where $J \geq 1$ is the dimension of Z_t. (i) Then*

$$\operatorname{avar}\left(n^{-1/2}\sum_{t=1}^{n} Z_t u_{t+1}\right) = \sigma_\varepsilon^4 M_{\pi,\lambda} \qquad \text{and} \qquad \operatorname*{plim}_{n\to\infty}\left(n^{-1}\sum_{t=1}^{n} Z_t x_t\right) = \sigma_y^2 V_\pi,$$

where $V_\pi = \left(\pi, \pi^2, \ldots, \pi^J\right)'$, and

$$M_{\pi,\lambda} = \tfrac{1}{1-\pi^2} B_1 + 2\lambda I + \lambda^2 B_2,$$

where I is the $J \times J$ identity matrix, and B_1 and B_2 are symmetric band matrices given by,

$$B_1 = \begin{pmatrix} 1 & \pi & \pi^2 & \cdots & \pi^{J-1} \\ \pi & 1 & \pi & \ddots & \vdots \\ \pi^2 & \pi & 1 & \ddots & \pi^2 \\ \vdots & \ddots & \ddots & \ddots & \pi \\ \pi^{J-1} & \cdots & \pi^2 & \pi & 1 \end{pmatrix}, \quad B_2 = \begin{pmatrix} 1+\pi^2 & -\pi & 0 & \cdots & 0 \\ -\pi & 1+\pi^2 & -\pi & \ddots & \vdots \\ 0 & -\pi & \ddots & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & -\pi \\ 0 & \cdots & 0 & -\pi & 1+\pi^2 \end{pmatrix}.$$

Within the class of instrumental variables, $\{z_t : z_t = Z_t'\alpha$ for some $\alpha \in \mathbb{R}^J\}$, the optimal instrument is given by

$$z_t^* = Z_t'\alpha_{\pi,\lambda}^*, \qquad \text{where} \qquad \alpha_{\pi,\lambda}^* = M_{\pi,\lambda}^{-1} V_\pi,$$

and the asymptotic variance of $\hat{\pi}^* = \hat{\pi}_{\mathrm{IV}_{z^*}}$ (the IV estimator that is associate with z_t^*) is

$$\operatorname{avar}\left\{n^{-1/2}(\hat{\pi}^* - \pi)\right\} = \frac{(1-\pi^2)^2}{V_\pi' M_{\pi,\lambda}^{-1} V_\pi} = \frac{1-\pi^2}{V_\pi'\left\{B_1 + 2\lambda(1-\pi^2)I + \lambda^2(1-\pi^2)B_2\right\}^{-1} V_\pi}.$$

Comment. Naturally, the optimal linear combination is scale invariant, in the sense that cz_t^* is also an optimal instrument for any $c \neq 0$.

2.2.1. *Implementation Multiple Variables IV*

The optimal linear combination depends on unknown parameters, so in our empirical application we will use a two-step estimation procedure. In the first step we obtain preliminary estimates of π and λ. For example, one can estimate π by a the two-stage least squares estimator and then estimate λ, by

$$\hat{\lambda}_{\hat{\pi}} = -\frac{\hat{\rho}_{\Delta x,1} + \frac{1-\hat{\pi}}{2}}{(1+\hat{\pi})\,\hat{\rho}_{\Delta x,1} + \frac{1+\hat{\pi}}{2}}, \tag{7}$$

where

$$\rho_{\Delta x,1} = \frac{\operatorname{cov}(\Delta x_t, \Delta x_{t-1})}{\operatorname{var}(\Delta x_t)}.$$

In the second step the instrument $z_t = Z_t'\alpha_{\hat{\pi},\hat{\lambda}}$ is computed and used to obtain new estimates of π and λ.[1] If necessary, the second step can be iterated until the estimates have converged. In our empirical application the estimates converged in just two iterations.

Note that the estimator in (7) simplifies to

$$\hat{\lambda}_{\text{LL}} = -\frac{\hat{\rho}_{\Delta x,1}}{2\hat{\rho}_{\Delta x,1} + 1},$$

when $\hat{\pi} = 1$, which is the estimator of $\lambda = \sigma_\eta^2/\sigma_\varepsilon^2$, in the the local level model

$$y_t = y_{t-1} + \varepsilon_t \qquad \text{and} \qquad x_t = y_t + \eta_t,$$

that is motivated by the fact that $\rho_{\Delta x,1} = -\frac{\lambda}{2\lambda+1}$ in this model, see e.g. Harvey (1993). When $|\pi| < 1$, $p = 1$ and $q = 0$, the estimator in (7) can be motivate by the identity

$$\rho_{\Delta x,1} = \frac{\operatorname{cov}(\Delta x_t, \Delta x_{t-1})}{\operatorname{var}(\Delta x_t)} = -\frac{\sigma_\varepsilon^2\left(\lambda + \frac{1-\pi}{1+\pi}\right)}{2\sigma_\varepsilon^2(\lambda + \frac{1}{1+\pi})} = -\frac{1}{2}\frac{(1+\pi)\,\lambda + (1-\pi)}{(1+\pi)\,\lambda + 1} = \frac{1}{2}\left\{\frac{\pi}{(1+\pi)\,\lambda + 1} - 1\right\}.$$

In our application we found this multiple variable IV estimator to be insensitive to the estimate of λ, and the point estimates of π were always very similar to the two-stage least squares estimates that does not require an estimate of λ.

2.2.2. *Related Estimators*

The instrumental variable estimator computed with z_t^* is based on the solution to an eigenvalue problem. This is a feature that is shared by the well known LIML estimator. Yet the two

[1] In the event that the estimator of π exceeds one we suggest to substitute 1 for $\hat{\pi}$ in the expression (7).

estimators are different, because the optimal estimator take full advantages of the particular covariance structure in this model.

In the stationary case $|\pi| < 1$, this optimal IV estimator, $\hat{\pi}^*$, will be similar to the TSLS estimator when λ is small. This follows from the fact that

$$n^{-1}\sum_{t=1}^{n} Z_t Z_t' \xrightarrow{p} \sigma_\varepsilon^2 \left(\tfrac{1}{1-\pi^2} B_1 + \lambda I\right) = \sigma_\varepsilon^2 \left(M_{\pi,\lambda} - \lambda I - \lambda^2 B_2\right),$$
$$n^{-1}\sum_{t=1}^{n} Z_t x_t \xrightarrow{p} \sigma_y^2 V_\pi,$$

when $|\pi| < 1$. So that the linear combination of instruments that is implied by the TSLS estimator, converges in probability to $\alpha_{\text{TSLS}} = \left(M_{\pi,\lambda} - \lambda I - \lambda^2 B_2\right)^{-1} V_\pi$, as $n \to \infty$. Which will be similar to $\alpha^* = M_{\pi,\lambda}^{-1} V_\pi$ when λ is small. Still the asymptotic variance of the TSLS estimator exceed that of the optimal instrument when $\lambda > 0$ in the stationary case $|\pi| < 1$.

2.2.3. *Quantifying the Asymptotic Variance*

In Figure 1 we have plotted the asymptotic variance for several estimators in the situation where $\pi = 0.975$ and $\lambda = 10$. This configuration is motivated by our empirical analysis that is presented in Section 4.

All these estimators are linear combinations of $Z_t = (x_{t-1} - \bar{x}_1, \ldots, x_{t-10} - \bar{x}_{10})'$, so the asymptotic variance is simply given by

$$\text{avar}(\hat{\pi}_{\alpha' Z_t}) = \frac{\alpha' M_{\pi,\lambda} \alpha}{(\alpha' V_\pi)^2}.$$

The line with the crossed symbols presents the asymptotic variance of the single-variable instrument, $\hat{\pi}_{\text{IV}_j}$, which has $z_t = x_{t-j} - \bar{x}_j$, for $j = 1, \ldots, 10$. In the notation given above, these estimators correspond to α-vectors that have one non-zero element, e.g. $\alpha = (1, 0, \ldots, 0)'$.

We also present results for the estimator that optimally combines a subset of the ten variable, specifically the optimal combination of the $J-j+1$ instruments $(x_{t-j} - \bar{x}_j, \ldots, x_{t-J} - \bar{x}_J)$, where $j = 1, 2, 3$ and $j \leq J \leq 10$. Obviously the smallest asymptotic variance (in this class of estimators) is achieved by the estimator that has $j = 1$ and $J = 10$. However, by increasing j the estimator becomes robust to measurement errors that are $(j-1)$-dependent. So we are interested in the loss of efficiency by dropping the first few lags as instruments. We are also interested in the marginal gains from increasing J. The reason is that theory suggests that J be as large as possible, but the practical implication of increasing J is that observations must be dropped from the sample. It is therefore useful to know that the efficiency gain from increasing J beyond 10, say, is small.

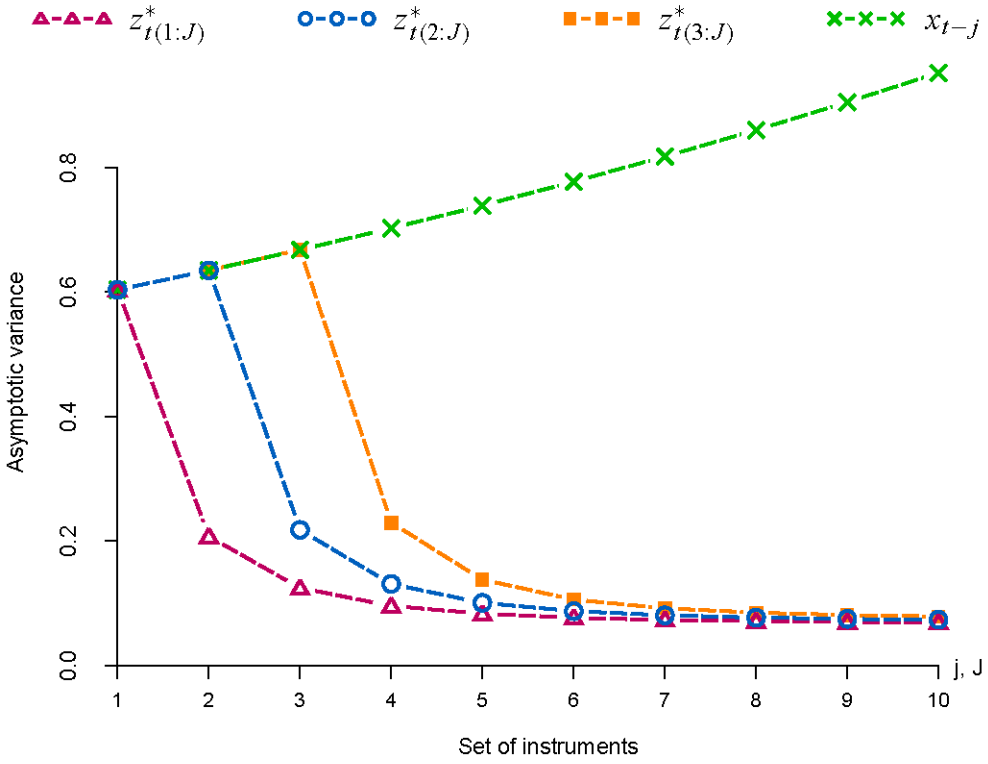

Figure 1: The asymptotic variance of the IV estimator based on different subset of instrumental variables. Crosses correspond to the single-variable instrument estimators where $z_t = x_{t-j} - \bar{x}_j$; triangles represent the optimal combinations of $(x_{t-1} - \bar{x}_1, \ldots, x_{t-J} - \bar{x}_J)$, for $J = 1, \ldots, 10$; circles and squares denote the optimal combinations of $(x_{t-2} - \bar{x}_2, \ldots, x_{t-J} - \bar{x}_J)$ and $(x_{t-3} - \bar{x}_3, \ldots, x_{t-J} - \bar{x}_J$, respectively. The results are for the case where $\pi = 0.975$ and $\lambda = 10$. We see a substantial gain in efficiency by constructing instruments as a combination of multiple lagged values of x_{t-j}. Omitting the first few lags of x_{t-j} is fairly innocuous when J is sufficiently large.

Figure 1 shows that there are substantial gains from combining multiple instruments, but that the loss of efficiency by dropping the first few instruments is modest in this configuration, once J is chosen large enough. Increasing J beyond ten only leads to very minor gains in efficiency. So our preferred instrumental variable estimation in our empirical analysis will be the one that combines lags four through ten.

2.3. **Properties of Estimators: The ARMA(p,q) Case**

Consider now the case where y_t is an ARMA(p,q), and where we allow for a more general specification for the measurement errors.

Theorem 4 *Suppose that Assumption 1 holds. When $\pi = 1$ we have for all $j \geq 0$,*

$$\hat{\pi}_{\mathrm{IV}_j} \xrightarrow{p} 1, \qquad as\ n \to \infty.$$

When $\pi < 1$ and $j \geq \max(p, q)$ we have

$$\hat{\pi}_{\mathrm{IV}_j} \xrightarrow{p} \frac{\gamma(j+1)}{\gamma(j)}, \qquad as\ n \to \infty,$$

where $\gamma(h) = \mathrm{cov}(y_t, y_{t+h})$, $h = 0, 1, \ldots$.

Previously we established the consistency of $\hat{\pi}_{\mathrm{IV}_j}$ for π when $p = 1$, $y_t \sim$AR(1) and the consistency holds in general in the unit root case $\pi = 1$. When $p \geq 2$ but $\pi < 1$ we see that the IV estimator, $\hat{\pi}_{\mathrm{IV}_j}$, is consistent for $\gamma(j+1)/\gamma(j)$. So the question is whether this ratio is related to the persistence parameter π. This is addressed next.

Lemma 3 *Suppose that Φ^m is positive for some integer m, then $\frac{\gamma(j+1)}{\gamma(j)} \to \pi$ as $j \to \infty$.*

The Lemma is a consequence of the Perron-Frobenius theorem, and the result shows, in conjunction with Theorem 4, that $\hat{\pi}_{\mathrm{IV}_j} \xrightarrow{d} \pi$ as $n, j \to \infty$. The convergence $\frac{\gamma(j+1)}{\gamma(j)} \to \pi$ occurs at a fast exponential rate that is defined by the second largest eigenvalue of Φ, which suggests that j does not have to be very large in practice. The assumption that Φ^m is positive for some m, is stronger than necessary, yet it is a reasonable assumption for the type of time series we consider in this paper. The assumption rules out cases where the largest eigenvalue is negative, which could induce cyclical behavior in the autocorrelation function.

2.4. **Multivariate Extension**

In some cases it may be desirable to estimate all the autoregressive parameters, $(\varphi_1, \ldots, \varphi_p)$, simultaneously. This is possible with the following class of multivariate IV estimators,

$$\hat{\varphi}_{\mathrm{IV}Z} = \left(\sum_{t=1}^{n} Z_t X_t' \right)^{-1} \sum_{t=1}^{n} Z_t x_{t+1},$$

where $X_t = (x_t, x_{t-1}, \ldots, x_{t-p+1})'$ and $Z_t = (x_{t-j} - \bar{x}_j, \ldots, x_{t-j-p+1} - \bar{x}_{j-p+1})'$.

Theorem 5 (multivariate instrumental variable estimator) *Suppose that Assumption 1 holds and $j \geq \max(p, q)$. Then*

$$\hat{\varphi}_{\mathrm{IV}Z} \xrightarrow{p} (\varphi_1, \ldots, \varphi_p)'.$$

Naturally, it is also possible to use an TSLS estimator that utilize more than p instrumental variables. It is also our experience that the multivariate IV estimators are sensitive to the

measurement errors. So with measurement errors of the magnitude we have in our empirical application with realized measures, it appears that an extremely large sample size is needed in order to get reliable estimates of all autoregressive parameters when $p \geq 2$.

Because we are mainly concerned with the persistence parameter and the autocorrelation function, we do not pursue these multivariate estimators further.

3. An Approximate Autocorrelation Function of A Latent Time Series

In this section we introduce an approximate estimator of the autocorrelation function that is based on a variant of the instrument variable estimator we studied in the previous Section. It is well know that measurement errors cause the population autocorrelation function of the observed process to look different from that of the underlying time series. With simple measurement errors, the autocorrelations of the observed process is simple those of the underlying process, scaled by a constant. In the context of realized measures this has been noted in Taylor (2005, pp. 337).

Before we define the new approximate autocovariance function for the latent y-process, we define the traditional empirical autocovariances for the latent process, y, and the observed process, x.

If y_t is observed then we can estimate the autocorrelations by the empirical autocorrelations that are defined by

$$\mathrm{ACF}_y(h) = \frac{\sum_{t=1}^{n} y_{t+h}(y_t - \bar{y}_0)}{\sum_{t=1}^{n} y_t(y_t - \bar{y}_0)}, \qquad h = 0, 1, \ldots.$$

The probability limit $\rho_y(h) = \mathrm{plim}_{n\to\infty} \mathrm{ACF}_y(h)$ is well defined whether $\pi = 1$ or $|\pi| < 1$. Naturally, $\mathrm{ACF}_y(h)$ is simply the least squares estimator in the regression

$$y_{t+h} = \rho_y(h) y_t + \mu_y + u_{t,h},$$

where μ_y is a constant. The corresponding regression equation for the observed time series is

$$x_{t+h} = \rho_x(h) x_t + \mu_x + v_{t,h},$$

where the errors-in-variables problem will cause the least squares estimator of $\rho_x(h)$, defined by

$$\mathrm{ACF}_x(h) = \frac{\sum_{t=1}^{n} x_{t+h}(x_t - \bar{x}_0)}{\sum_{t=1}^{n} x_t(x_t - \bar{x}_0)}, \qquad h = 0, 1, \ldots,$$

to be inconsistent for $\rho_y(h)$. In the presence of measurement errors it is therefore tempting to estimate $\rho_y(h)$ using an IV estimator, analogous to the way we have estimate the persistence parameter π. Consider

$$\mathrm{ACF}_x^*(h) = \frac{\sum_{t=1}^{n} z_t x_{t+h}}{\sum_{t=1}^{n} z_t x_t},$$

where the instrument z_t could be a lagged value of $x_{t-j} - \bar{x}_j$ or a linear combination of such $z_t = Z_t'\alpha$ with $Z_t = (x_{t-j} - \bar{x}_j, \ldots, x_{t-J} - \bar{x}_J)'$. The latter corresponds to a two-stage least squares estimator, where α is determined in the first stage by regressing x_t onto Z_t. In our empirical application we use $j = 4$ and $J = 10$.

We refer to $\text{ACF}_x^*(h)$, $h = 1, 2, \ldots$, as the approximate autocorrelation function, where the nomenclature "approximate" is due to the fact that $\text{ACF}_x^*(h)$ is not consistent for $\rho(h)$ in general. The potential inconsistency can be understood from the following simple example. Suppose that y_t is an AR(2) process with $|\pi| < 1$ and $z_t = x_{t-j} - \bar{x}_j$. Then $\text{ACF}_x^*(h) \xrightarrow{p} \gamma(h+j)/\gamma(j)$ which need not equal $\rho(h) = \gamma(h)/\gamma(0)$. However if the process is highly persistent, then

$$\frac{\gamma(h+j)/\gamma(j)}{\gamma(h)/\gamma(0)} \approx 1,$$

making $\text{ACF}_x^*(h)$ an approximate estimator of $\rho(h)$. Note that if y_t is an AR(1) process with $\pi \neq 0$ then $\gamma(h+j)/\gamma(j) = \gamma(h)/\gamma(0) = \pi^h$. So $\text{ACF}_x^*(h)$ is consistent for $\rho(h)$ in this case.

We illustrate the merits of the approximate autocorrelation function by considering two persistent AR(2) processes. That is measured with error. Specifically we consider the process

$$y_t = \varphi_\bullet(\tfrac{3}{4}y_{t-1} + \tfrac{1}{4}y_{t-2}) + \varepsilon_t,$$

where $\varepsilon_t \sim \text{iid}\, N(0,1)$ and where $\varphi_\bullet$ is either $\varphi_\bullet = 1$ (unit root) or $\varphi_\bullet = 1 - \frac{1}{\sqrt{n}}$ (local to unit root). The latter translates into $\pi = 0.949$, $\pi = 0.975$, and $\pi = 0.992$, for the sample sizes $n = 250$, $n = 1,000$, and $n = 10,000$, respectively.

We consider the autocorrelation functions for both y_t and $x_t = y_t + \eta_t$, where $\eta_t \sim \text{iid}\, N(0, \sigma_\eta^2)$ with $\sigma_\eta^2 = 4$. The corresponding results for $\sigma_\eta^2 = 1$ and $\sigma_\eta^2 = 10$ are presented in Figure 7 in Appendix B. The simulation results reported in Figure are based on 1,000 simulations where the initial values were set to $y_0 = y_{-1} = 0$.

The short-dashed lines in Figure 2 represent the population autocorrelation function for the underlying process. Naturally, for the unit root process in the left panels the population autocorrelation is constant and equal to one. The long-dashed lines represent the empirical autocorrelation function, ACF_x, that is computed with the observed time series, x_t, and the solid blue lines represent the new approximate autocorrelation function, ACF_x^*. For comparison we also include the empirical autocorrelation function, ACF_y, that is computed with underlying y-process (solid green lines). The difference between the empirical ACF_y and the population ACF reflects the well known bias that vanishes as $n \to \infty$. The empirical autocorrelations reported are the averages over 1,000 simulations.

For the unit root case in the left panels, it is interesting to note that the approximate autocorrelation function is a less biased measure of the population autocorrelation function than the (infeasible) empirical ACF_y, which is computed with the (in practice unobserved)

y_t process. This holds true for much higher levels of measurement errors (see Figure 7 in Appendix B for the corresponding results with $\sigma_\eta^2 = 10$). For the local to unit root process we see that that ACF_x^* is nearly as as good as the infeasible ACF_y in particular for large sample sizes, and it clearly dominates the traditional ACF_x.

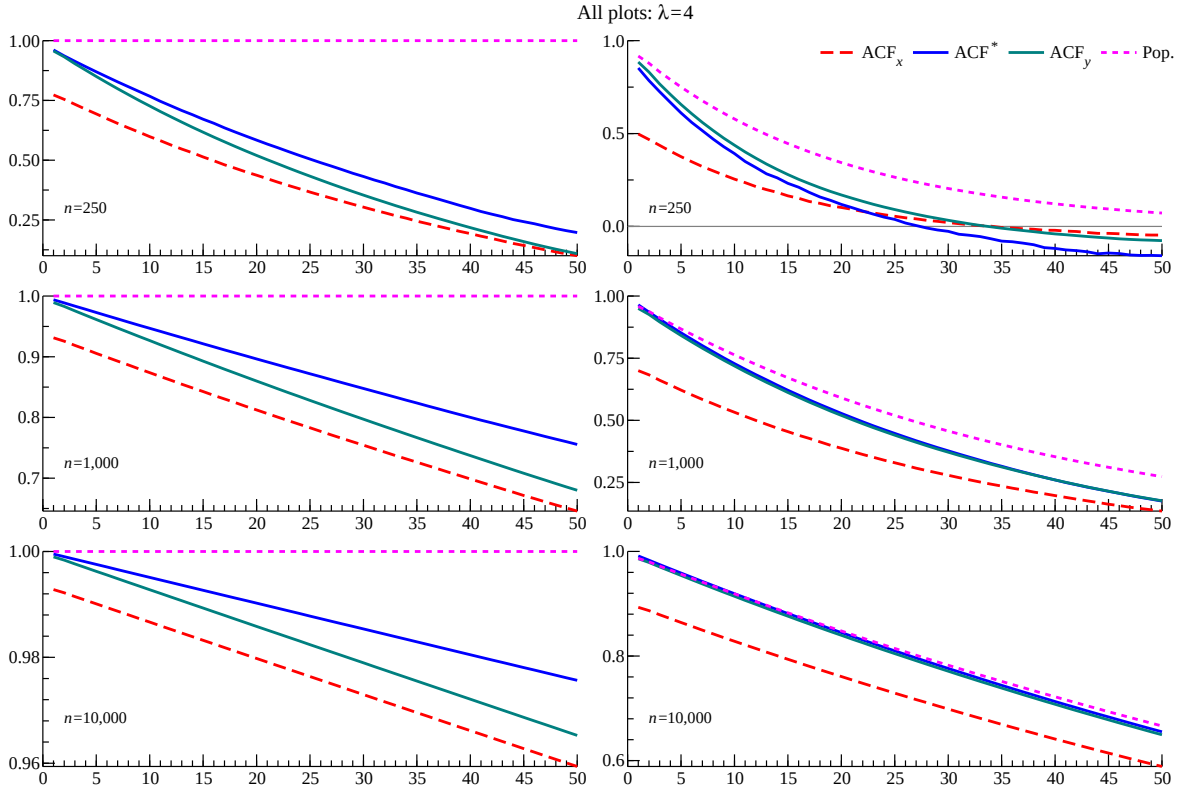

Figure 2: The short dashed lines represent the population autocorrelation function for the underlying autoregressive y-process (the object of interest). The long-dashed lines are the empirical autocorrelation functions for the observed x-process, ACF_x*. The solid blue line is the approximate autocorrelation function,* ACF_x^**, also computed with the observed x-process. For comparison we include* ACF_y *which is the (infeasible) empirical acf for the y-process (green lines).*

4. **Empirical Analysis of Realized Measures, Inflation, and Absolute Returns**

We present empirical results using three data sets. The first data set consists of realized measures of volatility for stocks in the Dow-Jones Industrial Average (DJIA) (as of medio 2008). We consider both the realized variance and the realized kernel. The second data set consists of two macroeconomic variables measuring US inflation. The third data set consists of two long time series of absolute returns.

We present two types of results. For the realized measures of volatility, we estimates the

persistence parameter, π, and compute both OLS and IV based unit root tests. For all three data sets we compute the approximate ACFs introduced in this paper, and compare it to the empirical ACF for the observed time series.

High-frequency based estimators of volatility are far more precise of volatility than squared returns, which is valuable for a number of reasons. For the purpose of evaluating volatility models, Andersen & Bollerslev (1998) documented that the realized variance strongly dominates squared returns when GARCH models are evaluated with Minzer-Zarnowitch regressions, see also Hansen & Lunde (2005*a*). On a related issue, Hansen & Lunde (2006) have shown that a precise proxy of the latent volatility is critical for the empirical ranking of volatility models to be consistent for the population ranking unless the loss function has certain properties. See also Patton (2008) and Patton & Sheppard (2009) who provide further insight about this issue.

A drawback of the realized variance is that it is sensitive to market microstructure noise, and it is therefore not sensible to compute the RV with ultra high frequency returns such as tick-by-tick returns. Robust estimators that can utilize the entire database more efficiently include those by Zhang, Mykland & Aït-Sahalia (2005), Barndorff-Nielsen et al. (2008*a*, 2009), and Hansen & Horel (2009). However, even these estimators are in practice found to have a sizable sampling error, as is evident from the confidence intervals that are reported for these estimators, see e.g. Barndorff-Nielsen et al. (2008*a*) and Hansen & Horel (2009). Any of these point estimates should therefore not be taken to be the true volatility. The sampling error must be accounted for when the objective is to learn about the dynamics of actual volatilities. Naturally, the measurement error can have other sources besides sampling error, such as those induced by market microstructure noise that has not properly been accounted for. The measurement error will be different for different realized measures, but the conclusions that one draws about y_t from each of them should not contradict one another, because they are all proxies for the same latent variable.

The importance of accounting for the measurement errors in the observed realized variances have been stressed by Andersen, Bollerslev, Diebold & Labys (2003) and Andersen, Bollerslev & Meddahi (2005). They emphasize the downwards bias in the R^2 that measurement errors induce in predictive regressions. See also Meddahi (2001*a*), Meddahi (2002), Andersen et al. (2004), Andersen, Bollerslev & Meddahi (2006).

Our basis setup where the realized variance is viewed as a noisy proxy of latent volatility has previously been used in Barndorff-Nielsen & Shephard (2002). Their objective was to estimate the parameters of the underlying stochastic volatility model. See also Bollerslev & Zhou (2002) and Barndorff-Nielsen et al. (2004).

4.1. **Data Description**

4.1.1. *Realized Measures of Volatility*

We analyze daily volatility estimates primarily based on high-frequency assets prices for 29 assets in the Dow Jones industrial average. The sample period runs from January 3, 2002 to July 31, 2009 with a total of 1,907 trading days for most of the series. The high frequency data used to compute the realized measures of volatility is the collection of trades and quotes recorded on the NYSE. These high frequency data were extracted from the TAQ database through the Wharton Research Data Services (WRDS) system. Both the realized kernel and the realized variance is computed with transaction prices. However, quote prices are being used to clean the transaction data for anomalies. We follow the step-by-step cleaning procedure proposed by Barndorff-Nielsen, Hansen, Lunde & Shephard (2009).

We did not include realized measures that were compute with high frequency data that spanned less than six hours. For each of the assets there were about 18 such days, primarily days where the market closed at noon, such as the day after Thanksgiving. These data were removed in order to eliminate obvious outliers that would arise from realized measures that correspond to just half a day of volatility. However, removing these data points barely affected any of our estimates.

4.1.2. *Other Data: Macroeconomic Time Series and Absolute Return Series*

We present the approximate autocorrelation functions for two time series of inflation and two time series of absolute returns. The two time series of inflation are those compute with "CPI-U, all items" (PUNEW) and the "headline personal consumption expenditure implicit price deflator" (GMDC). These are monthly time series (1959:M1 to 1997:M9) that have previously been analyzed in Stock & Watson (1999) and Hansen, Lunde & Nason (2009). The two time series of absolute returns are based on daily returns on the DJIA and the S&P 500 downloaded from Yahoo Finance. These span the period October 1, 1928 to September 16, 2009 and January 3, 1950 to September 16, 2009, respectively.

4.2. **The persistence of the underlying volatility**

In this Section we estimate the persistence parameter, π, using the instrumental variable estimators that were introduced in Section 2. The persistence parameter has been estimated in earlier work. For instance, Maheu & McCurdy (2002) estimated an ARMA(1,1) model with a daily time series of the realized variance for an exchange rate, and reported $\pi = 0.9$. Meddahi (2003) deduced the value, $\pi = 0.95$ from Bollerslev & Zhou (2002), who estimated stochastic volatility diffusions using empirical moments of the integrated variance. Interestingly, Boller-

slev & Zhou (2002) did mention the potential use of instrumental variables in the context of additive measurement errors, but did not pursue this estimation strategy. In an application with time-varying betas that were computed from daily returns, Ghysels & Jacquier (2006) used the first lag as an instrumental variable to estimate an augmented AR(1) model for the noisy time series of betas.

Table 1: Autoregressive Persistence Parameter, π. $x = \log(RK_t)$.

		Single variable IV				*Multiple variables IV*			
	OLS	IV_1	IV_2	IV_3	IV_4	$IV_{1:10}$	$IV_{2:10}$	$IV_{3:10}$	$IV_{4:10}$
AA	0.854	0.966	0.976	0.986	0.981	0.977	0.983	0.985	0.986
AXP	0.926	0.988	0.986	0.987	0.991	0.989	0.990	0.991	0.993
BA	0.832	0.960	0.972	0.987	0.994	0.976	0.984	0.988	0.989
BAC	0.942	0.978	0.985	0.992	0.994	0.984	0.989	0.992	0.993
C	0.938	0.978	0.985	0.991	0.987	0.983	0.988	0.990	0.989
CAT	0.845	0.949	0.975	0.987	0.994	0.971	0.983	0.987	0.987
CVX	0.850	0.953	0.967	0.984	0.989	0.968	0.977	0.981	0.980
DD	0.847	0.959	0.973	0.988	0.986	0.975	0.982	0.985	0.984
DIS	0.864	0.959	0.976	0.990	0.991	0.975	0.984	0.988	0.987
GE	0.902	0.975	0.984	0.992	0.991	0.984	0.989	0.991	0.991
GM	0.865	0.952	0.984	0.986	0.984	0.974	0.988	0.991	0.996
HD	0.850	0.964	0.968	0.992	0.989	0.977	0.983	0.988	0.986
HPQ	0.819	0.943	0.967	0.979	0.985	0.965	0.978	0.983	0.984
IBM	0.857	0.968	0.970	0.992	0.993	0.978	0.983	0.986	0.984
INTC	0.858	0.945	0.962	0.998	0.993	0.964	0.980	0.990	0.984
JNJ	0.827	0.944	0.982	0.986	0.982	0.970	0.984	0.986	0.987
JPM	0.927	0.972	0.982	0.993	0.989	0.981	0.987	0.991	0.990
KO	0.836	0.965	0.967	0.984	0.991	0.976	0.981	0.985	0.985
MCD	0.751	0.933	0.955	0.988	0.976	0.963	0.977	0.986	0.986
MMM	0.809	0.946	0.946	0.994	0.967	0.962	0.972	0.982	0.978
MRK	0.751	0.899	0.980	0.972	0.980	0.946	0.977	0.976	0.979
MSFT	0.866	0.965	0.977	0.990	0.981	0.978	0.984	0.986	0.985
PFE	0.793	0.935	0.942	0.991	1.002	0.959	0.975	0.991	0.989
PG	0.800	0.928	0.964	0.973	0.992	0.955	0.973	0.979	0.981
T	0.832	0.940	0.958	0.978	0.984	0.959	0.973	0.983	0.986
UTX	0.825	0.955	0.967	0.972	0.988	0.969	0.976	0.980	0.983
VZ	0.848	0.962	0.971	0.982	0.989	0.975	0.982	0.987	0.989
WMT	0.813	0.952	0.961	0.991	0.980	0.970	0.979	0.986	0.985
XOM	0.850	0.954	0.967	0.987	0.985	0.969	0.977	0.982	0.978

Point estimates of the persistence parameter π. The first column contains the least squares estimator. The next four columns are IV estimates based on a single-variable instruments: $x_{t-2} - \bar{x}_2, \ldots, x_{t-5} - \bar{x}_5$, respectively. The next four columns are estimates using multiple instrumental variables, $x_{t-i} - \bar{x}_i, \ldots, x_{t-10} - \bar{x}_{10}$, for $i = 2, \ldots, 5$.

We use $y_t = \log \mathrm{IV}_t$ and $x_t = \log \mathrm{RM}_t$, where RM_t is a realized measure. We prefer the logarithmic transformed variables for two reasons. First, it gets around the problem that the ARMA model does not prevent volatility from being negative. Second, in the BNS framework the asymptotic variance of $\mathrm{RV}_t - \mathrm{IV}_t$ is proportional to $\mathrm{IQ}_t = \int_{t-1}^{t} \sigma_s^4 \mathrm{d}s$, whereas the asymptotic variance of $\log \mathrm{RV}_t - \log \mathrm{IV}_t$ is proportional to $\mathrm{IQ}_t / \mathrm{IV}_t^2$. The latter varies less with t, so the log-transformation leads to less heteroskedasticity.

In Tables 1-2 we present least squares and IV estimates of the persistence parameter. The estimates in Table 1 are those for the time series with realized kernel estimates. For each of the 29 assets we compute the least squares estimator and eight instrumental variable estimators. The first four IV estimates are single variable instruments based on the instrument $z_t = x_{t-j} - \bar{x}_j$, where $j = 1, \ldots, 4$. The last four IV estimates are based on multiple lags of the observed process, $x_{t-j} - \bar{x}_j, \ldots, x_{t-10} - \bar{x}_{10}$, $j = 1, \ldots, 4$, and these are compute with the procedure described in Section 2.2.1.

The least squares estimates in the first column are 10-20% smaller than the IV estimators in most cases. This shows that stochastic bias is important despite the large sample size. Thus interpreting the asymptotic result that the stochastic bias is of order $O_p(n^{-1})$ to mean that this bias is negligible is very misleading in this context. We see that the persistence parameter tends to be large when the first few lags of x_{t-j} is not used as an instrument. Because a large value of j offers a higher degree of robustness there is strong evidence that $j = 1$ (and $j = 2$ in some cases) is too small to properly estimate π. The multiple variable estimators with $j = 3$ and $j = 4$ are very similar and close to one in all cases, which shows that the underlying time series is highly persistent and close to unit root.

In Table 2 we present empirical results that are analogous to those in Table 1. The only difference being that these are based on the realized variance computed with 30 minute returns instead of the realized kernel. The realized variance is expected to be a less accurate estimator of the quadratic variation than the realized kernel, which translates in to a larger measurement error variance. This indeed found to be the case, because the bias of the least squares estimator is about twice as large as that we observed for with the realized kernel. The IV estimates based on the realized variance are strikingly similar to those we obtained with the realized kernel. This is further evidence that the underlying is highly persistent and close to being unit root. The average difference (across assets) between the estimates obtained with the realized kernel and those obtained with the realized variance are reported in the last row of Table 2. For the instrumental variable estimators we get very similar estimates in all cases, whereas the two least squares estimates are quite different. These observations reflect that the IV estimators are estimating the persistence of the same underlying time series, whereas the least squares estimators are affected by the variance of the measurement errors that is larger for the realized

variance than the realized kernel.

Table 2: Autoregressive Persistence Parameter, π. $x = \log(RV_t)$.

		Single variable IV				*Multiple variables IV*			
	OLS	IV_1	IV_2	IV_3	IV_4	$IV_{1:10}$	$IV_{2:10}$	$IV_{3:10}$	$IV_{4:10}$
AA	0.722	0.953	0.974	0.991	0.982	0.978	0.984	0.986	0.987
AXP	0.853	0.982	0.990	0.989	0.984	0.990	0.991	0.992	0.993
BA	0.659	0.967	0.969	0.965	0.985	0.980	0.984	0.989	0.994
BAC	0.887	0.964	0.985	0.990	0.993	0.980	0.990	0.992	0.993
C	0.881	0.975	0.991	0.990	0.985	0.986	0.990	0.990	0.990
CAT	0.701	0.976	0.948	0.999	0.983	0.981	0.983	0.987	0.985
CVX	0.698	0.948	0.971	0.965	0.976	0.970	0.975	0.978	0.982
DD	0.716	0.941	0.998	0.989	0.965	0.978	0.987	0.984	0.985
DIS	0.746	0.953	0.980	0.983	1.002	0.980	0.988	0.990	0.991
GE	0.820	0.973	0.979	0.986	0.992	0.985	0.988	0.991	0.993
GM	0.758	0.945	0.966	0.974	0.983	0.973	0.985	0.993	1.001
HD	0.706	0.976	0.952	0.999	0.976	0.981	0.984	0.988	0.987
HPQ	0.670	0.927	0.952	0.967	0.971	0.960	0.972	0.979	0.983
IBM	0.708	0.973	0.968	0.999	0.982	0.982	0.984	0.985	0.984
INTC	0.725	0.935	0.971	0.994	0.977	0.970	0.982	0.984	0.983
JNJ	0.715	0.936	0.978	0.977	0.965	0.969	0.980	0.982	0.985
JPM	0.842	0.969	0.979	0.991	0.989	0.983	0.988	0.991	0.991
KO	0.708	0.967	0.959	0.989	0.990	0.980	0.984	0.988	0.989
MCD	0.626	0.896	0.966	0.985	0.969	0.956	0.979	0.984	0.986
MMM	0.639	0.931	0.948	1.027	0.930	0.968	0.979	0.984	0.977
MRK	0.611	0.895	0.991	0.955	0.975	0.957	0.976	0.973	0.980
MSFT	0.750	0.955	0.986	0.977	0.976	0.978	0.983	0.984	0.986
PFE	0.651	0.910	0.916	1.004	1.037	0.958	0.981	0.999	0.993
PG	0.639	0.916	0.939	0.997	0.999	0.960	0.976	0.984	0.980
T	0.709	0.941	0.948	0.969	0.998	0.967	0.978	0.987	0.991
UTX	0.685	0.962	0.957	0.986	0.982	0.976	0.980	0.984	0.984
VZ	0.719	0.960	0.973	0.974	0.990	0.978	0.983	0.986	0.989
WMT	0.650	0.941	0.975	0.977	0.986	0.974	0.982	0.984	0.986
XOM	0.709	0.963	0.953	0.973	0.985	0.972	0.975	0.980	0.981
Average difference between π-estimates based on RK and RV									
Ave.	0.127	0.005	0.003	0.002	0.004	-0.003	-0.001	-0.000	-0.001

Point estimates of the persistence parameter π. The first column contains the least squares estimator. The next four columns are IV estimates based on a single-variable instruments: $x_{t-2} - \bar{x}_2, \ldots, x_{t-5} - \bar{x}_5$, respectively. The next four columns are estimates using multiple instrumental variables, $x_{t-i} - \bar{x}_i, \ldots, x_{t-10} - \bar{x}_{10}$, for $i = 2, \ldots, 5$. The last row displays the average difference (across assets) between the estimates obtained with the realized kernel and the realized variance.

The unit root test statistics, $n(\hat{\pi} - 1)$, that arises from our estimates of π using the realized kernel estimates are reported in Table 3. The first column is the traditional Dickey-Fuller

t-statistic. These typically range between -150 and -400 that suggest overwhelming evidence against the unit root hypothesis. However, as we have seen earlier, the least squares estimates of the persistence parameter, π, have a substantial bias, which causes these test statistics to be misleading. The test statistics based on the IV estimates offer a more accurate picture of the evidence against the unit root hypotheses.

Table 3: Unit Root Test Statistics: $n(\hat{\pi}-1)$. $x=\log(RK_t)$.

		Single variable IV				*Multiple variables IV*			
	OLS	IV_1	IV_2	IV_3	IV_4	$IV_{1:10}$	$IV_{2:10}$	$IV_{3:10}$	$IV_{4:10}$
AA	-276	-65.0	-46.0	-25.6	-35.8	-42.5	-32.2	-27.5	-26.5
AXP	-140	-23.5	-26.9	-25.2	**-16.3**	-21.2	**-19.3**	**-16.3**	**-13.3**
BA	-317	-75.2	-52.4	-25.1	**-12.0**	-44.2	-30.1	-22.3	-21.6
BAC	-110	-42.3	-27.9	**-16.0**	**-11.5**	-30.1	**-20.2**	**-14.6**	**-13.9**
C	-117	-42.4	-28.5	**-16.1**	-24.5	-31.1	-22.6	**-18.9**	**-20.0**
CAT	-293	-95.6	-46.4	-24.6	**-11.6**	-54.8	-31.3	-24.2	-25.1
CVX	-283	-89.1	-61.6	-30.7	-21.5	-60.6	-43.4	-34.9	-38.1
DD	-289	-76.8	-50.9	-23.0	-27.0	-47.7	-34.1	-27.8	-29.4
DIS	-257	-77.6	-46.0	**-19.1**	**-16.1**	-47.6	-30.2	-23.2	-25.2
GE	-185	-47.7	-30.4	**-15.1**	**-17.7**	-29.9	-21.1	**-17.4**	**-17.7**
GM	-247	-87.7	-28.6	-26.5	-29.0	-48.2	-22.2	**-16.5**	**-7.93**
HD	-282	-68.1	-60.0	**-14.6**	**-20.3**	-44.1	-32.3	-23.0	-26.0
HPQ	-326	-102	-58.6	-37.0	-27.5	-62.5	-39.8	-31.4	-29.6
IBM	-270	-59.7	-55.8	**-15.8**	**-13.6**	-40.8	-32.4	-25.9	-30.3
INTC	-268	-103	-71.4	**-3.92**	**-13.6**	-67.4	-38.2	**-18.7**	-29.9
JNJ	-326	-106	-34.8	-26.4	-33.1	-56.3	-29.2	-26.3	-25.2
JPM	-138	-52.5	-34.4	**-12.6**	**-20.1**	-36.5	-23.7	**-16.8**	**-19.5**
KO	-309	-65.8	-62.5	-30.9	**-17.8**	-45.5	-36.1	-27.6	-27.6
MCD	-469	-127	-84.6	-23.5	-44.4	-69.9	-42.3	-26.2	-25.6
MMM	-361	-103	-102	**-11.8**	-62.1	-72.3	-53.2	-34.0	-40.6
MRK	-469	-191	-37.2	-53.3	-38.0	-101	-42.4	-44.9	-40.2
MSFT	-254	-66.8	-42.7	**-19.2**	-35.0	-42.2	-30.5	-26.1	-27.8
PFE	-391	-123	-109	**-16.4**	**2.94**	-77.6	-46.3	**-17.5**	-20.9
PG	-378	-136	-68.1	-50.9	**-14.3**	-83.7	-50.1	-39.1	-35.1
T	-315	-113	-79.4	-41.4	-30.1	-77.0	-50.4	-31.9	-26.5
UTX	-330	-85.0	-62.3	-52.0	-23.3	-58.8	-45.5	-36.8	-31.5
VZ	-286	-72.4	-55.5	-33.3	**-20.7**	-46.5	-33.7	-24.6	-20.8
WMT	-352	-90.9	-73.2	**-16.2**	-36.8	-56.1	-38.7	-26.2	-28.9
XOM	-284	-86.6	-62.9	-23.9	-28.0	-58.9	-42.4	-34.3	-40.6

The 1% and 5% critical values are -20.7 and -14.1, respectively (see e.g. Fuller (1996, Table 10.A.1, page 641)). Test statistics in bold font are those that are insignificant at the 1% level.

The test statistics in bold font are those for which we fail to reject the unit root hypothesis at the 1% level. While the unit root hypothesis is rejected for most series, it is evident that the

empirical evidence against the unit root hypothesis is less clear-cut than suggested by the OLS-based unit root tests. The conclusion we draw from our estimates of the persistence parameter is that the underlying process is highly persistent. This may be attribute to the underlying process being local to unit root, fractionally integrated, or some other form of persistent process. Naturally, the usual suspect "structural change" cannot be ruled out either.

4.3. **Empirical ACFs for Realized Measures**

We consider two time series with estimates of daily volatility. The first time series is based on realized variance, computed with 30 minute returns, the other is computed with the realized kernel estimator implemented as detailed in Barndorff-Nielsen et al. (2009). Both the realized variance and the realized kernel are estimates of the quadratic variation. Thus we can view both as noisy proxies of the same population quantity, the underlying quadratic variation. We compute the approximate autocorrelations ACF_x^* using the two-stage least squares estimator discussed in Section 3, where seven lags, $x_{t-4}, \ldots, x_{t-10}$, are used as instrumental variables.

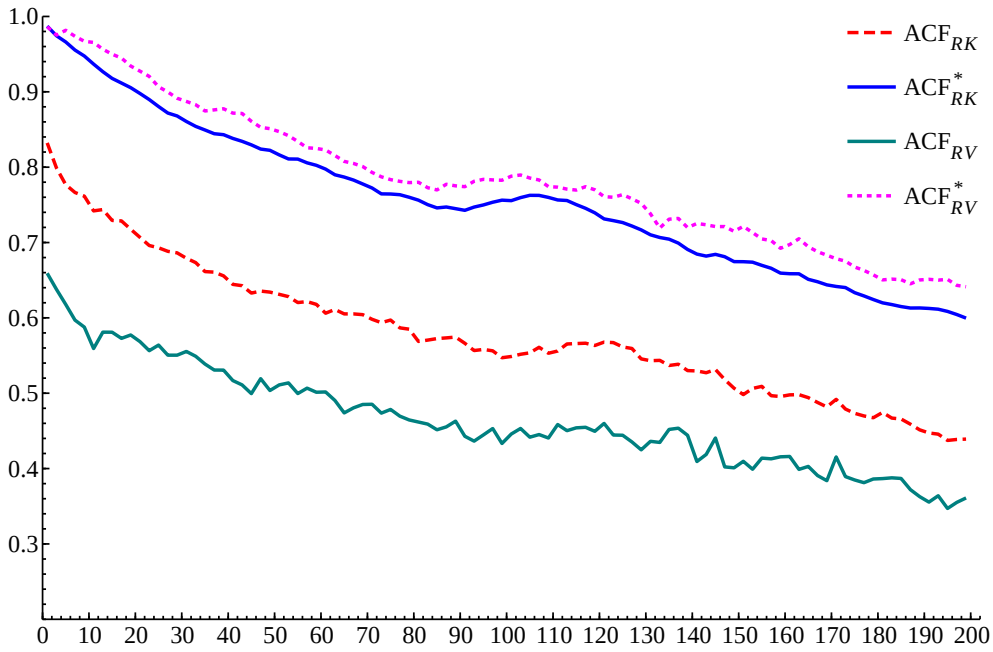

Figure 3: The empirical and approximate autocorrelation functions computed with realized measures of volatility for BA. The approximate ACF^* *better reflects the autocorrelation function of latent volatility. While the conventional ACF are quite different the two* ACF^**-estimates are in agreement.*

Figure 3 displays the estimated autocorrelation functions for realized measures of volatility

compute with high frequency returns on BA (The Boeing Company). The two upper curves are the approximate autocorrelation function, ACF*, based on the realized kernel and the realized variance. The approximate ACF is designed to reflect the the persistence of the latent time series, which – in this case – is the same underlying volatility process for both time series. The ACF*-estimates for the two time series are quite similar, precisely as one would expect because the realized variance and the realized kernel are both estimates of the same underlying quantity. The two lower curves in Figure 3 are computed with the traditional empirical autocorrelation function, ACF$_x$, and the realized kernel and the realized variance result in distinctly different ACF$_x$-estimates. The difference between the two simply reflects that the measurement errors in the two series are different. Figure 4 gives another example of the estimated autocorrelation functions with another asset MRK (Merck & Co., Inc). The ACF for all other assets are very similar to those presented in Figures 3-4.

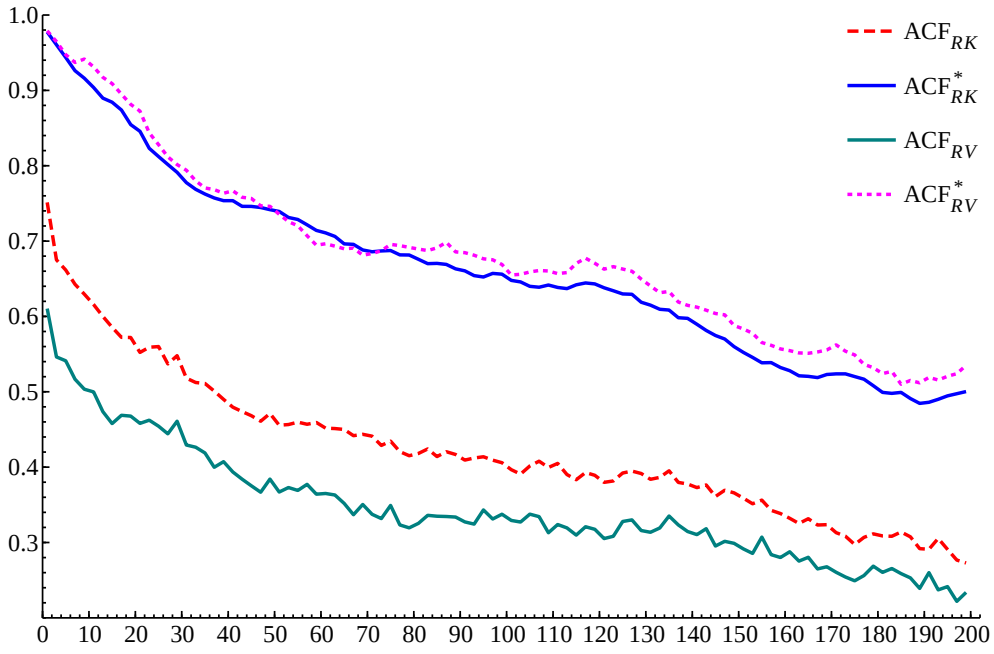

Figure 4: The empirical and approximate autocorrelation functions computed with realized measures of volatility for MRK. The approximate ACF* *better reflects the autocorrelation function of latent volatility. Again we see that the conventional ACF are quite different whereas the two* ACF**-estimates are in agreement.*

In a survey of the existing literature, Taylor (2005) noted that the autocorrelation function for the realized variance is typically estimated to start out between 0.60 and 0.65 and decay

slowly, precisely as is the case for the conventional autocorrelation estimates for the realized variance in Figures 3 and 4. Taylor (2005, sec. 12.9.4) discusses the downwards bias that measurement errors induce on ACF_x, and he speculates that the first-order autocorrelation of the underlying volatility may be 0.70 or larger. We estimate the first-order autocorrelation of the underlying volatility to be very close to unity in all cases, so the downwards bias is far more severe than may have been thought.

The traditional ACFs suggest that the realized kernel is somewhat more persistent than the realized variance, for both BA and MRK. A point we want to emphasize here, is that this discrepancy between the two ACFs is induced by the realizes variance being a less accurate estimator of the latent volatility, and that neither of the conventional autocorrelation functions properly reflects the persistence of the population measure of volatility. The persistence is better assessed with our approximate estimation of the autocorrelation function, ACF^*, that produces very similar estimates for the realized kernel and the realized variance.

Given the results we reported in Figure 2 we see that the evidence against the unit root hypothesis is less clear-cut than suggested by the conventional autocorrelation function. Since the estimated autocorrelations are downwards biased when the underlying population quantity is close to one, the estimated ACF^*s are by no means strong evidence against the unit root hypothesis. When taking the finite sample bias and sampling error into account the estimated ACF^* could be consistent with a unit root process, a fractionally integrated process, as well as many other types of processes.

4.4. **Autocorrelation Functions for Time-Series of Inflation**

In Figure 5 we have computed the empirical autocorrelation function, ACF_x, and the approximate estimator, ACF_x^*, for two monthly time series of inflation. These are virtually identical which suggests that the measurement errors in these time series are relatively small.

4.5. **Empirical Analysis of Absolute Returns**

Absolute returns is often used as an example of a process that has properties that resemble those of a fractionally integrated process, see Ding, Granger & Engle (1993). Squared returns is a simple one-to-one transformation of absolute returns, so if absolute returns has long memory features, then so will squared returns. In fact, the autocorrelation functions for log-absolute returns and log-squared returns are identical. It is perhaps puzzling that the case of long memory is rarely made about squared returns, even though the order of fractional integration, d, is the same for absolute returns and squared returns, see e.g. Andersen & Bollerslev (1997), Harvey (1998), and Bollerslev & Wright (2001). We believe that the explanation for this is

that either series can be viewed as noisy measurements of volatility, and that the noise is simply more pronounced in squared returns, which conceals the persistence to a larger extend than is the case for absolute returns. The eigenfunction analysis, see Meddahi (2001*b*) and Andersen, Bollerslev & Meddahi (2010), provides the deeper theoretical explanation for this. For instance, in the context of stochastic volatility models this phenomenon would naturally arise if the instantaneous volatility equals the first eigenfunction, as is the case in Forsberg & Ghysels (2007).

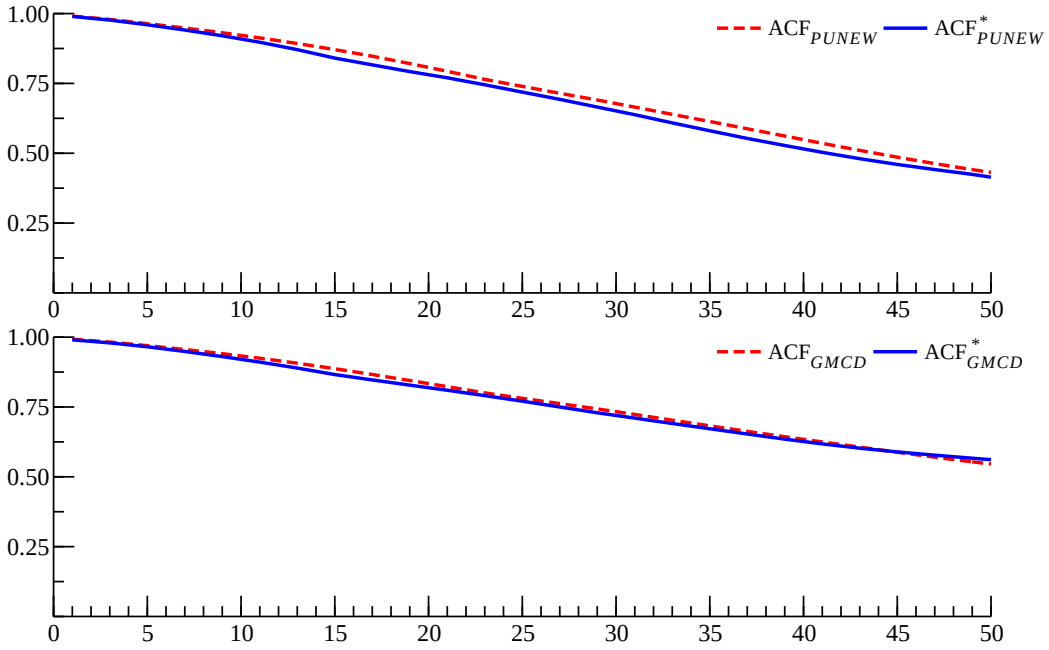

Figure 5: ACF for inflation series.

In Figure 6 we have computed the empirical autocorrelation function for absolute returns as well as the approximate autocorrelation function. These are distinctly different. The empirical autocorrelation function is often interpreted as evidence of long memory, and sometimes considered to be evidence against an unit root hypothesis. The new estimation of the autocorrelation of the underlying process, ACF^*_x, reveals that the choice between long memory and unit root is less clear-cut than is suggested by the conventional autocorrelation function for the observed process, ACF_x.

Relying on the empirical ACF for the observed series is perhaps not the best way to classify the long-dependence properties of a time series, because it is influenced by the short-

run dynamics. A better classification scheme of persistent processes is that of Muller & Watson (2008). Their method is explicitly designed to filter the effect of short-run dynamics and focus on the variation at low frequencies. In their empirical analysis of absolute returns, they do find empirical evidence that supports a fractionally integrated model for absolute returns.

Long memory models that explicitly account for noise in the manner we discuss in this paper is a relatively unexplored topic. A few papers such as, Chong & Lui (1999), Sun & Phillips (2003), Hurvich, Moulines & Soulier (2005) and Haldrup & Nielsen (2007), consider estimation of the memory parameter in an ARFIMA setting, where the time series of interest is perturbed by an additive noise term. In the context of volatility measures, Bollerslev & Wright (2000) showed that high-frequency based volatility measures lead to more accurate estimates of the long-memory parameter. This is quite intuitive because the use of realized volatility measures effectively amounts to reducing the measurement error.

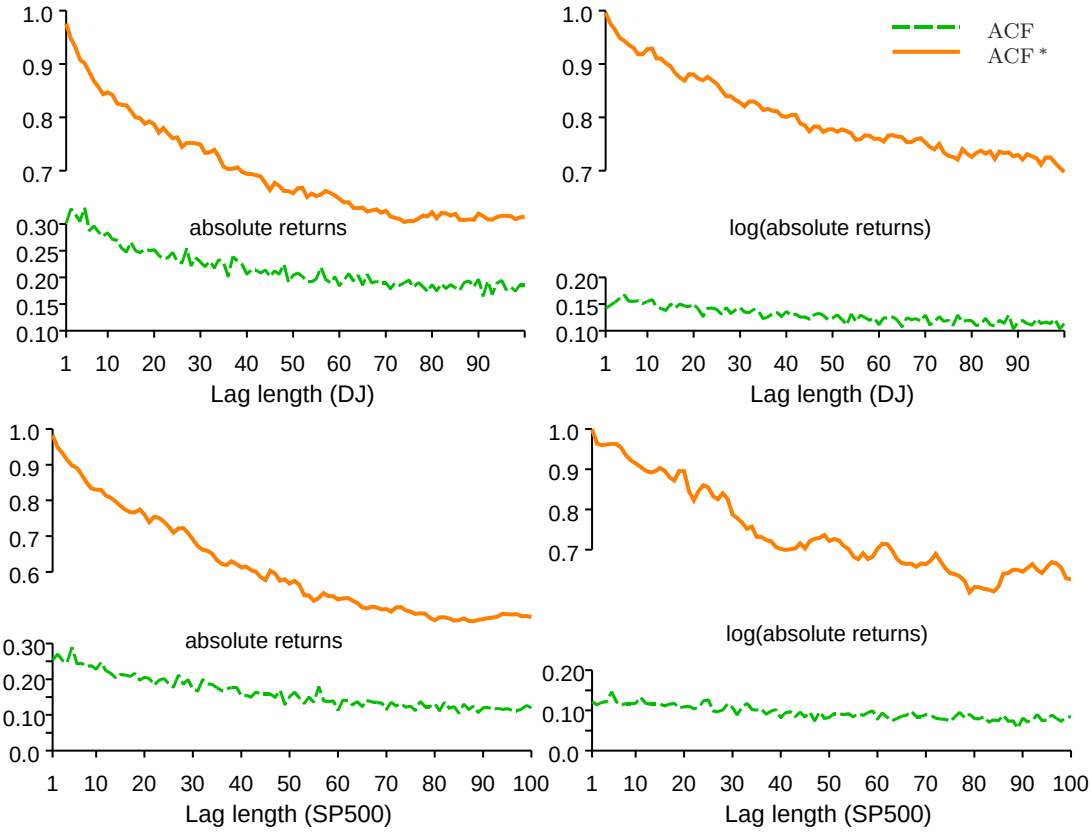

Figure 6: ACF for daily absolute return.

5. Summary and Concluding Remarks

In a situation where a time series is observed with measurement errors, we have shown that the persistence of the underlying time series can be assessed by instrumental variable methods. When the latent time series is an ARMA(p,q) process it is possible to estimate the autoregressive parameters consistently, hence a consistent estimate of the persistence parameter. The instrumental variable we employ are lagged values of the observed time series, and we derived the optimal linear IV estimator in a special case.

Serial dependence makes the lagged values of the observed time series useful as instruments. So a highly persistent latent time series leads to an ideal framework for the instrumental variable estimators. On the other hand, a time series with a small autocorrelation causes the lagged values to be weak instruments, and the IV estimators may be unreliable in such circumstances.

We have also proposed a novel estimator of the autocorrelation function for the underlying time series. This estimator also relies on lagged values of the observed process being good and valid instruments. So this estimator is best suited for the case where the underlying time series is persistent.

We have shown that measurement errors can conceal the persistence of the underlying time series, and that unit root tests are unreliable unless the measurement errors are accounted for. So the empirical evidence against the unit root hypothesis may, in some cases, not have been as clear-cut as may have been believed. Our findings are also relevant for multivariate time series. For instance, the fact that a unit root process with measurement errors can be confused with a fractionally integrated process begs the following question: Can some of the fractional cointegration results that have been documented in the literature be attributed to measurement errors? Another plausible explanation is that the underlying time series are individually integrated of order one and cointegrate in the traditional sense, but that measurement errors make the individual time series appear to be fractionally integrated. In any case, we believe it is important to account for measurement errors in applications with realized measures of volatility, and other persistent time series with similar levels of measurement errors.

Appendix A: Proofs

Proof of Lemma 1. By premultiplying (2) by $\varphi(L)$ we have

$$\varphi(L)x_t = \varphi(L)y_t + \varphi(L)\xi + \varphi(L)\eta_t = \varphi(L)(y_t - \delta) + (1-\pi)(\delta + \xi) + \varphi(L)\eta_t,$$

where we have used that $\varphi(L)c = (1-\pi)c$ for any constant c. Now substitute (1) to get

$$\varphi(L)x_t = (1-\pi)(\delta + \xi) + \theta(L)\varepsilon_t + \varphi(L)\eta_t.$$

□

Proof of Lemma 2. The result for $\text{var}(y_t)$ is well known. For $h = 0$ we have $\text{var}(x_t) = \text{var}(y_t + \eta_t) = \sigma_y^2 + \sigma_\eta^2$, and for $h \neq 0$ we have

$$x_t - \xi - \delta = y_t - \delta + \eta_t = \pi^h(y_{t-h} - \delta) + \sum_{i=0}^{h-1} \pi^i \varepsilon_{t-i} + \eta_t,$$

so that

$$\text{cov}(x_t, x_{t-h}) = E\left[\left\{\pi^h(y_{t-h} - \delta) + \sum_{i=0}^{h-1} \pi^i \varepsilon_{t-i} + \eta_t\right\}\{(y_{t-h} - \delta) + \eta_{t-h}\}\right] = \pi^h \text{var}(y_{t-h}).$$

□

Proof of Theorem 1. The case with $|\pi| < 1$ follows from Lemma 2. When $\pi = 1$ we have $y_{[un]}/\sqrt{n} \xrightarrow{w} \sigma_\varepsilon W_u$ where W_u is a standard Brownian motion, $u \in [0, 1]$, and we consider

$$\begin{aligned}
&n^{-1}\sum_{t=1}^{n}(x_t - \bar{x}_0)(\varepsilon_{t+1} + \eta_{t+1} - \eta_t) = n^{-1}\sum_{t=1}^{n}(y_t - \bar{y}_0 + \eta_t - \bar{\eta})(\varepsilon_{t+1} + \eta_{t+1} - \eta_t) \\
&= n^{-1}\sum_{t=1}^{n}(y_t - \bar{y}_0)\varepsilon_{t+1} - n^{-1}\sum_{t=1}^{n}(\eta_t - \bar{\eta})^2 + n^{-1}\sum_{t=1}^{n} y_t\eta_{t+1} - n^{-1}\sum_{t=0}^{n-1} y_{t+1}\eta_{t+1} \\
&- \bar{y}_0 n^{-1}\sum_{t=1}^{n}(\eta_{t+1} - \eta_t) + n^{-1}\sum_{t=1}^{n}(\eta_t - \bar{\eta})(\varepsilon_{t+1} + \eta_{t+1}),
\end{aligned}$$

where

$$\begin{aligned}
n^{-1}\sum_{t=1}^{n} y_t\eta_{t+1} - n^{-1}\sum_{t=0}^{n-1} y_{t+1}\eta_{t+1} &= -n^{-1}\sum_{t=0}^{n-1}(y_{t+1} - y_t)\eta_{t+1} + n^{-1}(y_n\eta_0 - y_0\eta_0) \\
&= -n^{-1}\sum_{t=1}^{n}\varepsilon_t\eta_t + O_p(n^{-1}) = o_p(1),
\end{aligned}$$

and $\bar{y}_0 n^{-1}\sum_{t=1}^{n}(\eta_{t+1} - \eta_t) + n^{-1}\sum_{t=1}^{n}(\eta_t - \bar{\eta})(\varepsilon_{t+1} + \eta_{t+1}) = o_p(1)$. Similarly,

$$n^{-2}\sum_{t=1}^{n}(x_t - \bar{x}_0)^2 = n^{-2}\sum_{t=1}^{n}(y_t - \bar{y}_0)^2 + o_p(1),$$

so that

$$\begin{aligned}
n(\hat{\pi}_{\text{LS}} - 1) &= \frac{n^{-1}\sum_{t=1}^{n}(x_t - \bar{x}_0)(\varepsilon_{t+1} + \eta_{t+1} - \eta_t)}{n^{-2}\sum_{t=1}^{n}(x_t - \bar{x}_0)x_t} \\
&= \frac{n^{-1}\sum_{t=1}^{n}(y_t - \bar{y}_0)\varepsilon_{t+1} + n^{-1}\sum_{t=1}^{n}\eta_t^2 - n^{-1}\sum_{t=1}^{n}\varepsilon_{t+1}\eta_{t+1} + o_p(1)}{n^{-2}\sum_{t=1}^{n}(y_t - \bar{y}_0)^2 + o_p(1)} \\
&\xrightarrow{d} \frac{\int_0^1 (W_u - \bar{W})\text{d}W_u - \sigma_\eta^2/\sigma_\varepsilon^2}{\int_0^1 (W_u - \bar{W})^2\text{d}u}.
\end{aligned}$$

□

Lemma A.1 *Let Σ_t be short for $n^{-1/2}\sum_{t=1}^{n}$. Given Assumption 1 with $p=1$ and $q=0$ we have for $j\geq 1$ and $d\geq 0$*

$$\operatorname{cov}\left(\Sigma_t x_{t-j}u_{t+1},\Sigma_t x_{t-j-d}u_{t+1}\right)\to\sigma_\varepsilon^4\times\begin{cases}\frac{1}{1-\pi^2}+2\lambda+(1+\pi^2)\lambda^2 & d=0,\\ \frac{\pi}{1-\pi^2}-\pi\lambda^2 & d=1,\\ \frac{\pi^d}{1-\pi^2} & d\geq 2,\end{cases}$$

as $n\to\infty$

Proof. Without loss of generality we set $\delta=\xi=0$. In our proof we use that

$$\Sigma_t y_{t-j}\eta_t=\Sigma_t(\pi y_{t-j-1}+\varepsilon_{t-j})\eta_t=\pi\Sigma_t y_{t-j-1}\eta_t+\Sigma_t\eta_t\varepsilon_{t-j}+O_p(n^{-1/2}). \tag{A.1}$$

We have

$$\begin{aligned}\Sigma_t x_{t-j}u_{t+1}&=\Sigma_t(y_{t-j}+\eta_{t-j})\left(\varepsilon_{t+1}+\eta_{t+1}-\pi\eta_t\right)=\Sigma_t y_{t-j}\varepsilon_{t+1}+\Sigma_t\eta_{t-j}\varepsilon_{t+1}\\&+\Sigma_t y_{t-j}\eta_{t+1}-\pi\Sigma_t y_{t-j}\eta_t+\Sigma_t\eta_{t-j}(\eta_{t+1}-\pi\eta_t)\overset{(A.1)}{=}\Sigma_t y_{t-j}\varepsilon_{t+1}+\Sigma_t\eta_{t-j}\varepsilon_{t+1}\\&+\Sigma_t y_{t-j}\eta_{t+1}-\pi^2\Sigma_t y_{t-j}\eta_{t+1}-\pi\Sigma_t\varepsilon_{t-j+1}\eta_t+\Sigma_t\eta_{t-j+1}(\eta_{t+1}-\pi\eta_t)\\&+O_p(n^{-1/2})=\Sigma_t y_{t-j}\varepsilon_{t+1}+\Sigma_t\eta_{t-j+1}\varepsilon_{t+1}-\pi\Sigma_t\eta_t\varepsilon_{t-j+1}+(1-\pi^2)\Sigma_t y_{t-j}\eta_{t+1}\\&+\Sigma_t\eta_{t-j+1}(\eta_{t+1}-\pi\eta_t)+O_p(n^{-1/2})=\Sigma_t y_{t-j}\left\{\varepsilon_{t+1}+(1-\pi^2)\eta_{t+1}\right\}\\&+\Sigma_t\eta_{t-j+1}(\varepsilon_{t+1}+\eta_{t+1}-\pi\eta_t)-\pi\Sigma_t\eta_t\varepsilon_{t-j+1}+O_p(n^{-1/2}),\end{aligned}$$

which is a sum of uncorrelated terms. So the asymptotic variance is

$$\begin{aligned}\operatorname{avar}(\Sigma_t x_{t-j}u_{t+1})&=\sigma_y^2\left\{\sigma_\varepsilon^2+(1-\pi^2)^2\sigma_\eta^2\right\}+\sigma_\eta^2\left\{\sigma_\varepsilon^2+(1+\pi^2)\sigma_\eta^2\right\}+\pi^2\sigma_\eta^2\sigma_\varepsilon^2\\&=\tfrac{\sigma_\varepsilon^4}{1-\pi^2}+(1-\pi^2)\sigma_\varepsilon^2\sigma_\eta^2+(1+\pi^2)\sigma_\eta^2\sigma_\varepsilon^2+(1+\pi^2)\sigma_\eta^4\\&=\tfrac{\sigma_\varepsilon^4}{1-\pi^2}+2\sigma_\varepsilon^2\sigma_\eta^2+(1+\pi^2)\sigma_\eta^4=\sigma_\varepsilon^4\left\{\left(1-\pi^2\right)^{-1}+2\lambda+\left(1+\pi^2\right)\lambda^2\right\}.\end{aligned}$$

Next we analyze the covariances. The σ_ε^4-terms are given by

$$\begin{aligned}&\operatorname{cov}(\Sigma_t y_{t-j}\varepsilon_{t+1},\Sigma_t y_{t-j-d}\varepsilon_{t+1})\\&=\operatorname{cov}\left\{\Sigma_t\left(\pi^d y_{t-j-d}+\varepsilon_{t-j}+\cdots+\pi^{d-1}\varepsilon_{t-j-d+1}\right)\varepsilon_{t+1},\Sigma_t y_{t-j-d}\varepsilon_{t+1}\right\}\\&=\pi^d\operatorname{var}(\Sigma_t y_{t-j-d}\varepsilon_{t+1})+\operatorname{cov}\left\{\Sigma_t\left(\varepsilon_{t-j}+\cdots+\pi^{d-1}\varepsilon_{t-j-d+1}\right)\varepsilon_{t+1},\Sigma_t y_{t-j-d}\varepsilon_{t+1}\right\}\\&=\pi^d\operatorname{var}(\Sigma_t y_{t-j-d}\varepsilon_{t+1})\to\pi^d(1-\pi^2)^{-1}\sigma_\varepsilon^4,\quad\text{as } n\to\infty.\end{aligned}$$

The $\sigma_\eta^2\sigma_\varepsilon^2$-terms are given by $\Sigma_t\eta_{t-j}\varepsilon_{t+1}-\pi\Sigma_t\eta_t\varepsilon_{t-j}+(1-\pi^2)\Sigma_t y_{t-j}\eta_{t+1}=\Sigma_t\eta_{t-j}\varepsilon_{t+1}-\pi\Sigma_t\eta_t\varepsilon_{t-j}+(1-\pi^2)\Sigma_t\left(\pi^d y_{t-j-d}+\varepsilon_{t-j}+\cdots+\pi^{d-1}\varepsilon_{t-j-d+1}\right)\eta_{t+1}$ such that

$$\operatorname{cov}\left\{\Sigma_t\eta_{t-j}\varepsilon_{t+1}-\pi\Sigma_t\eta_t\varepsilon_{t-j}+(1-\pi^2)\,\Sigma_t y_{t-j}\eta_{t+1},\Sigma_t\eta_{t-j-d}\varepsilon_{t+1}-\pi\Sigma_t\eta_t\varepsilon_{t-j-d}\right.$$

$$+(1-\pi^2)\Sigma_t y_{t-j-d}\eta_{t+1}\Big\} = (1-\pi^2)^2\pi^d \mathrm{var}(\Sigma_t y_{t-j-d}\eta_{t+1})$$
$$+ \mathrm{cov}\left\{-\pi\Sigma_t\eta_t\varepsilon_{t-j-d}, (1-\pi^2)\Sigma_t\pi^{d-1}\varepsilon_{t-j-d+1}\eta_{t+1}\right\}$$
$$= (1-\pi^2)\pi^d\sigma_\eta^2\sigma_\varepsilon^2 - (1-\pi^2)\pi^d\sigma_\eta^2\sigma_\varepsilon^2 = 0.$$

Finally, when $d=1$ the σ_η^4-term is simply

$$\mathrm{cov}(\Sigma_t\eta_{t-j}\eta_{t+1} - \pi\Sigma_t\eta_{t-j}\eta_t, \Sigma_t\eta_{t-j-1}\eta_{t+1} - \pi\Sigma_t\eta_{t-j-1}\eta_t)$$
$$= \mathrm{cov}(\Sigma_t\eta_{t-j}\eta_{t+1}, -\pi\Sigma_t\eta_{t-j-1}\eta_t) = -\pi\sigma_\eta^4 + o(1),$$

whereas this term is zero when $d \geq 2$. □

Proof of Theorem 2. With an AR(1) specification for y_t we have

$$x_t = \pi x_{t-1} + (1-\pi)(\delta+\xi) + \varepsilon_t + \eta_t - \pi\eta_{t-1}.$$

Without loss of generality we set $\delta = \xi = 0$. By repeated substitution $x_t = \pi^j y_{t-j} + \varepsilon_t + \pi\varepsilon_{t-1} + \cdots + \pi^{j-1}\varepsilon_{t-j+1} + \eta_t$, and it follows that

$$\mathrm{cov}(x_t, x_{t-j}) = \pi^j \mathrm{cov}(y_{t-h}, x_{t-h}) = \pi^j \mathrm{var}(y_{t-h}) = \pi^j\sigma_y^2.$$

Next, we consider the decomposition

$$\hat{\pi}_{\mathrm{IV}_j} = \frac{\sum_{t=1}^n (x_{t-j}-\bar{x}_j)x_{t+1}}{\sum_{t=1}^n (x_{t-j}-\bar{x}_j)x_t} = \pi + \frac{\sum_{t=1}^n (x_{t-h}-\bar{x}_h)\left(\varepsilon_{t+1}+\eta_{t+1}-\pi\eta_t\right)}{n^{-1}\sum_{t=1}^n (x_{t-h}-\bar{x}_h)x_t}.$$

From Lemma A.1 it follows that

$$\mathrm{avar}\left\{n^{-1/2}\sum_{t=1}^n (x_{t-j}-\bar{x}_j)\left(\varepsilon_{t+1}+\eta_{t+1}-\pi\eta_t\right)\right\} = \sigma_\varepsilon^4\left\{\tfrac{1}{1-\pi^2} + 2\lambda + (1+\pi^2)\lambda^2\right\},$$

and that

$$n^{-1}\sum_{t=1}^n (x_{t-j}-\bar{x}_j)x_t \xrightarrow{p} \pi^j\sigma_y^2 = \pi^j\tfrac{\sigma_\varepsilon^2}{1-\pi^2},$$

so that

$$n^{1/2}(\hat{\pi}_{\mathrm{IV}_j} - \pi) \xrightarrow{d} N(0, \sigma^2_{\hat{\pi}_{\mathrm{IV}_j}}),$$

where

$$\sigma^2_{\hat{\pi}_{\mathrm{IV}_j}} = \sigma_\varepsilon^4\left\{\tfrac{1}{1-\pi^2} + 2\lambda + (1+\pi^2)\lambda^2\right\}\left(\frac{\pi^j}{1-\pi^2}\sigma_\varepsilon^2\right)^{-2}$$
$$= \pi^{-2j}\left\{1-\pi^2+2\left(1-\pi^2\right)^2\lambda + \left(1-\pi^2\right)\left(1-\pi^4\right)\lambda^2\right\}$$

The proof for the case where $\pi = 1$ is given by Hall (1989). □

Proof of Theorem 3. The structure of the $J \times J$ matrix $M_{\pi,\lambda}$ follows from Lemma A.1 and V_π follows from the law of large numbers and the fact that $\mathrm{cov}(x_{t-j}, x_t) = \pi^j\sigma_y^2$ for $j \geq 1$.

We seek a vector, α, that solves

$$\min_{\alpha \in \mathbb{R}^J} \frac{\alpha' M_{\pi,\lambda} \alpha}{(\alpha' V_\pi)^2}.$$

This problem is clearly invariant to rescaling of α, so we can reformulate the problem as

$$\min_{\alpha} \alpha' M_{\pi,\lambda} \alpha, \qquad \text{s.t. } \alpha' V_\pi = 1.$$

The first order conditions are simply $2M_{\pi,\lambda}\alpha - \rho V_\pi = 0$, where ρ is the Lagrange multiplier, so that

$$\alpha^\star = \frac{1}{V_\pi' M_{\pi,\lambda}^{-1} V_\pi} M_{\pi,\lambda}^{-1} V_\pi,$$

is the solution to the constrained problem. By the scale invariance of α we have that $\alpha^* = cM_{\pi,\lambda}^{-1}V_\pi$ yields an optimal instrument for any $c \neq 0$. □

Proof of Theorem 4. For the unit root case the result follows from n

$$n^{-2} \sum_{t=1}^{n} (x_{t-j} - \bar{x}_j) x_t = \int_0^1 (W(u) - \bar{W})^2 \mathrm{d}u + o_p(1),$$

and

$$n^{-2} \sum_{t=1}^{n} (x_{t-j} - \bar{x}_j) x_{t+1} - n^{-2} \sum_{t=1}^{n} (x_{t-j} - \bar{x}_j) x_t = n^{-2} \sum_{t=1}^{n} (x_{t-j} - \bar{x}_j) \Delta x_{t+1} = o_p(1),$$

for any $j \geq 1$. When $\pi < 1$ the result follows from

$$\begin{aligned} n^{-1} \sum_{t=1}^{n} (x_{t-j} - \bar{x}_j) x_t &= n^{-1} \sum_{t=1}^{n} (y_{t-j} - \bar{y}_j + \bar{\eta})(y_t + \xi + \eta_t) \\ &= n^{-1} \sum_{t=1}^{n} (y_{t-j} - \bar{y}_j) y_t + o_p(1) = \rho_j + o_p(1). \end{aligned}$$

□

Proof of Lemma 3. For a positive matrix, A, with spectral radius r, we know from the Perron-Frobenius theorem that $A^k/r^k \to ab'$ as $k \to \infty$, where a and b are the (left and right) eigenvectors associated with the largest eigenvalue of A, which equals the spectral radius, r. Moreover, the elements of the vector a are all strictly positive.

Define the vector of p consecutive autocorrelations, $\gamma_j^* = (\gamma_j, \ldots, \gamma_{j-p+1})'$. Since π is the spectral radius of Φ then $(\pi^{-1}\Phi)^k \gamma_j^*$ converges to a limit that is proportional to the eigenvector a as $k \to \infty$. By the Yule-Walker equation we have

$$\gamma_{j+1} = \varphi_1 \gamma_j + \cdots + \pi_p \varphi_{j-p+1},$$

which implies that $\gamma_{j+1}^* = \Phi \gamma_j^*$. Thus if we define the vector $v_j = \pi^{-j} \gamma_j^* \in \mathbb{R}^p$, then $v_{j+1} = (\pi^{-1}\Phi) v_j$. This shows that v_j, as $j \to \infty$, approaches the eigenvector associated with π, which

implies that $v_{j+1} - \pi v_j \to 0$ as $j \to \infty$. By considering the first elements of the vectors v_{j+1} and v_j, (which are non-zero because a is strictly positive) it now follows that $\pi^{-j+1}\gamma_{j+1} - \pi^{-j}\gamma_j \to 0$, so that $\gamma_{j+1}/\gamma_j \to \pi$. □

Proof of Theorem 5. Consider the case where $|\pi| < 1$. Since $J \geq \max(p, q)$ we have

$$n^{-1}\sum_{t=1}^{n} Z_t X_t' \xrightarrow{p} \mathbf{\Gamma}_J = \begin{pmatrix} \gamma_J & \gamma_{J-1} & \cdots & \gamma_{J-p+1} \\ \gamma_{J+1} & \gamma_J & & \gamma_{J-p+2} \\ \vdots & & \ddots & \vdots \\ \gamma_{J+p-1} & \gamma_{J+p-2} & \cdots & \gamma_J \end{pmatrix}$$

$$n^{-1}\sum_{t=1}^{n} Z_t x_{t+1} \xrightarrow{p} \gamma_{J+1} = (\gamma_{J+1}, \gamma_{J+2}, \ldots, \gamma_{J+p})'.$$

So the IV estimator converges in probability to $\operatorname{plim}_{n\to\infty} \hat{\varphi}_{\mathrm{IV}\,Z} = \mathbf{\Gamma}_J^{-1}\gamma_{J+1}$. Next, by the Yule-Walker equations we have

$$\gamma_{J+1} = \mathbf{\Gamma}_J \varphi, \text{ where } \varphi = (\varphi_1, \ldots, \pi_p)',$$

and it now follows that the probability limit is given by $\varphi = (\varphi_1, \ldots, \varphi_p)'$. When $\pi = 1$ the proof follows by combining unit root results with those given above. □

Appendix B: Additional Plots

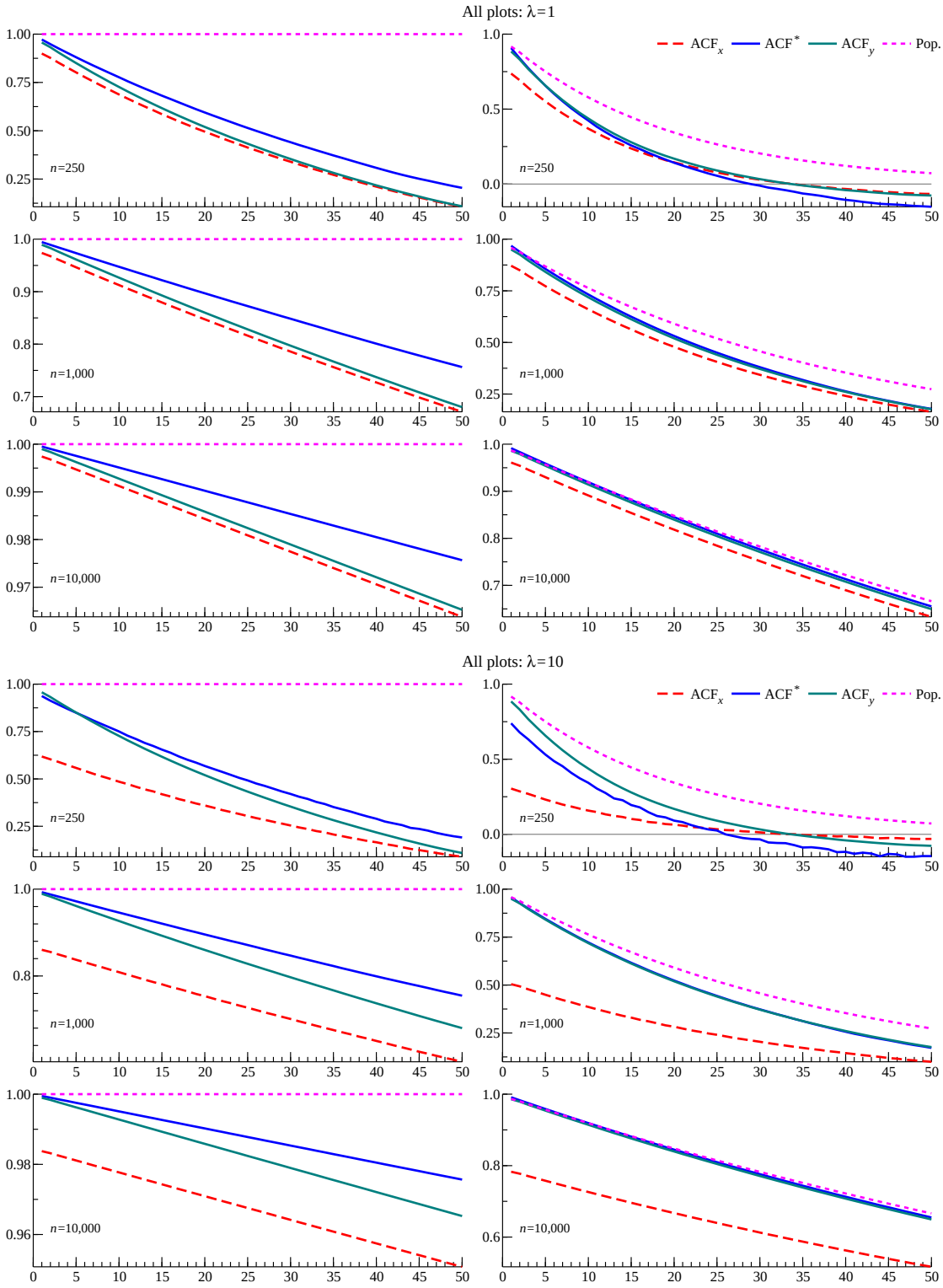

Figure 7: The figure present the ACFs ...

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