Cross-Section Regressions in Time Compressed Data: Estimating the Effect of Warming Temperature on Growth

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Abstract

To learn about the effects of warming temperature on growth, it is quite common to transform the data by taking the difference of two centered moving average, thereby removing the time dimension of a $T \times N$ panel. Taking as starting point that temperature data are not stationary, this paper studies the properties of time compressed data and their implications for regression with focus on K period averaging. We establish that the cross-section variance of the averaged data 'fans out' with K if the data are I(1). We then show that a correctly specified cross-section regression in the averaged data can yield $\sqrt{N}K$ consistent and asymptotically normal estimates of many quantities of economic interest. With full sample averaging, a super-consistent rate of $\sqrt{N}T$ can be obtained without having to deal with unit-root asymptotics. Averaging belongs to a class of time-compressed functions that magnify the signal in the I(1) regressor while diluting the stationary regression noise to give $\sqrt{N}K$ consistent estimates, and still allow $\sqrt{N}$ consistent estimates when the regressors are I(0). The result of general interest is that time compression can overcome the challenge of non-standard inference when the regressors are highly persistent.

Keywords: climate change, non-stationarity, fanning out, long-difference regressions.

JEL Classification: C2, Q5

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1 Introduction

There is increased policy interest in learning about the effects of climate change on economic outcomes. In economic models, the short-run response is the effect that follows a shift in the climate with expectations, beliefs, and investment held fixed, while the long-run response is the effect after both expectations and investments have adjusted to the new climate. However, these model concepts do not have a direct mapping in regressions. Concerns were raised over early cross-section regressions that omitted variables could bias the estimate of the long-run effect, also known as long-run multiplier. More recent works use short T panels in fixed-effect estimation but are worried that such estimates would not reflect longer term effects. This motivates using long-differences (LD) of time averaged data to estimate longer-term impacts from cross-section regressions, thereby compressing the time dimension. Empirical results often find the short and longer-term estimates to be similar. See, for example, discussion in Kolstad and Moore (2020), Dell et al. (2014, p.778), Carleton et al. (2024, Section 3.1), Hsiang (2016).

This paper considers a class of time-compression functions of which using data from only one period and time averaging are members. Our point of departure is the result in Deaton and Paxson (1994) that income inequality will increase with age if individual incomes (in logs) are random walks, with the implication that the cross-section variance of a non-stationary panel will 'fan-out' over time. We consider a more general non-stationary setup and show that the cross-section variance of a panel with N units over a span of K periods will increase at rate K with a pre-factor that depends on $\mathbb{E}_i[\omega_i^2]$, the mean over units of the spectral density at frequency zero of innovations. This implies that if we can only take a slice of the data from a $T \times N$ panel, taking data from the last sample period, T, will have the most variability.

We then consider time compression by averaging the data over time. Time averaging is commonly thought to remove high frequency noise, making it easier to visualize patterns at the cost of creating spurious dynamics.[1] This is true in the stationary case. It turns out that with non-stationary data, the cross-section variance still fans out at rate K, but shrinks by a factor of $1/3$ relative to point sampling at period K. While the shrinkage seems undesirable, using time averaged data in regressions has the effect of increasing signal in the I(1) regressor while reducing noise in the error variance. We show that the cointegrating vector estimated from a cross-section

[1] For example, the recession indicator of Sahm (2019), also known as Sahm rule, is based on a three-month moving average of the unemployment rate relative to its low in the prior 12 months. In the empirical growth literature, it is common to look at average growth rates over 5 or 10-years.

regression of a correctly specified static model is $\sqrt{N}K$ and asymptotically normal, and a rate of $\sqrt{N}T$ can be obtained with full sample averaging. It thus achieves fast convergence while retaining the convenience of standard normal inference. When the regressor is I(0), the estimate from the cross-section regression remains consistent and asymptotically normal, but converges at the standard rate of $\sqrt{N}$. Unlike time series regressions, the transition of the asymptotic distribution from I(0) to I(1) is smooth.

We also analyze the case when y is generated by a ADL(1,1) model. If the regressor is I(1), a static regression will yield $\sqrt{N}K$ consistent and asymptotically normal estimates of the long-run multiplier. If we estimate an ADL(1,1) model, the coefficients on x and its lag are $\sqrt{N}K$ consistent for any K while the coefficient on the lagged dependent variable has a Nickell bias that vanishes with K. In the I(0) case, the Nickell bias does not vanish but all other estimates are $\sqrt{N}$ consistent. Thus, estimates of coefficients relating to x are consistent and asymptotically normal whether or not x is stationary.

The smooth transition of the asymptotic distributions from I(0) to I(1) is possible not only with simple averaging, but for a class of time compressed functions with smooth weights on the innovations that can be characterized by a survival function. Super-consistency follows from the fact that time compression magnifies the signal in the I(1) regressor to make endogeneity and misspecification bias of second order, while asymptotic normality irrespective of whether the data are I(1) or I(0) follows when the weights on the innovations are continuous in the persistence parameter. Though the LD is not a member in this class, it also yields super consistent estimates in the I(1) case and is in fact more efficient than simple averaging. However, in the I(0) case and especially when the series is mildly persistent, it abandons information in all but the observations in a small neighbourhood, and discontinuous weights implicit in the LD prohibits an analysis of the stationary and non-stationary case within a unifying framework.

The paper proceeds as follows. Section 2 begins with the key insight in Deaton and Paxson (1994). Section 3 analyzes time compression by K period averaging. Section 4 analyzes the implications for regressions. Section 5 summarizes the results for a class of time compressed functions and relaxes the assumption of strict exogeneity. Section 6 analyzes long-differencing. Simulations are presented in Section 7. Section 8 concludes.

2 Cross-Section Variations at T when x_{it} is Non-Stationary

Climate economists think of weather observations x_t like temperature as a draw from a climate distribution. If the climate distribution is time invariant with mean μ, we may write $x_t = \mu + w_t$, where $w_t \sim (0, \sigma^2)$ is stationary. But a constant μ is at odds with the data that appear to be trending.[2] The top panel of Figure 1 takes x_t to be the U.S temperature data from 1895-2022 along with the fit from a (local level) model that allows for a stochastic trend. We see that the data (in black) has a mean around 56^0F until the 1970s when it started to drift upwards, increasing to a mean of 59^0F in 2022. The bottom graph plots the series (in black) for New York. In dotted red is the first principal component in a panel of demeaned data for the 50 states. For the state of New York, this component accounts for 83% of the total variation over time. Also plotted is the trend fitted to of the common component. Both plots indicate a slowly evolving trend.[3] The local-level model the factor model both have reduced form $\Delta x_{it} = \epsilon_{it} + \vartheta_i \epsilon_{it-1}$. For the U.S. data in the top panel of Figure 1, $\vartheta = -0.8133$. For the New York data in the bottom panel, $\vartheta = -0.8578$. The negative value of ϑ will be relevant in what follows.

The effects of x_t on y_t at different horizons can be of interest, and one that has drawn attention is the long-run effect. This parameter is often estimated by a long-difference (LD) regressions. Given a $T \times N$ panel of data, an LD regression first takes the long-difference of the time averages of y and x, on the ground that the data transformation will better isolate the slowly evolving variations. Averaging and differencing collapse the time dimension to perform a cross-section regression. We will use the term 'time compression' when the time diemension of the panel is removed.

2.1 The Fanning Out of Cross-Section Variations

Our first objective is to understand the cross-section variability of I(1) data in a panel of N (or S) non-stationary series observed over T periods. We will use $\text{var}_i(x_{i,T_0})$ to denote cross-section variance of x_{it} at $t = T_0$.

Our point of departure is the result in Deaton and Paxson (1994) that if utility is quadratic and the permanent income hypothesis (PIH) holds, consumption and income inequality will increase with age t. The result arises because consumption (c) is a random walk under PIH and can be

[2]Non-stationarity is modeled in, for example, Kolstad and Moore (2020, p.16), Nath et al. (2024, footnote 12), and Estrada et al. (2023). It is also considered in Kolstad and Moore (2020) and Hsiang (2016), Auffhammer (2018), Kolstad and Moore (2020), Carleton et al. (2024).

[3]The non-parametric approach of Mueller and Watson (2017) gives very similar estimates.

characterized as $c_{it} = c_{it-1} + e_{it}$. Assuming in addition that $\text{cov}(c_{i,t-1}, e_{it}) = 0$, the cross-section variance of a given set of N individuals in an age cohort at time t is related to the one in $t-1$ by $\text{var}_{i|t}(c_{it}) = \text{var}_{i|t-1}(c_{it-1}) + \sigma_i^2$. It follows that the cross-section variance of the cohort will increase with t (or age), reflecting the cumulative differenecs in individual shocks over time. Ng (2008) shows that if a fraction κ of the panel is non-stationary, the cross-section variance will still fan out with t, but at rate κ.

Deaton and Paxson (1994) noted that other preferences may increase or decrease consumption dispersion over time, and it can even be nullified if individuals are homogeneous. We now explore the fanning out effect outside of the PIH context, and under more general conditions. Specifically, we relax the random walk assumption to allow x_{it} to be a unit root process with serially correlated noise. Consider $\Delta x_{it} = C_i(L)u_{it}$, where $x_{i0} = 0$ and $u_{it} \sim (0, \sigma_i^2)$ is a white noise error, $C_i(L) = 1 + C_{i1}L + C_{i2}L^2 + \ldots$ is a polynomial in the lag operator L, possibly of infinite order with $\sum_{j=0}^{\infty} C_{ij}^2 < \infty$. Using $C_i(L) = C_i(1) + (1-L)C_i^*(L)$, where $C_i(1) = \sum_{j=0}^{\infty} C_{ij}$ and $C_{ij}^* = -\sum_{k=j+1}^{\infty} C_{ik}$, the Beveridge-Nelson Decomposition yields

$$x_{it} = C_i(1)\sum_{s=1}^{t} u_{is} + C_i^*(L)e_{it} = C_i(1)\sum_{s=1}^{t} u_{is} + w_{it}.$$

In the above, x_{it} is decomposed into a random walk (non-stationary) component $C_i(1)\sum_{j=1}^{t} u_{ij} + C_i^*(L)u_{it}$ and a mean-reverting (stationary) component $w_{it} = C_i^*(L)u_{it}$. For a given i, the variance of x_{it} at $t = T_0$ is

$$\text{var}(x_{i,T_0}) = C_i(1)^2\sigma_i^2 T_0 + \text{var}(w_{i,T_0}).$$

Provided that $C_i(1)^2 \neq 0$, this variance will diverge with T_0. The cross-section variance at $t = T_0$ is given by

$$\text{var}_i(x_{i,T_0}) = \mathbb{E}_i[C_i(1)^2\sigma_i^2] \cdot T_0 + \text{var}_i[w_{i,T_0}] = O(T_0).$$

In the random walk case, w_{it} is absent and the divergence of the cross-section variance with t is guaranteed. If we were to select data from a particular t_* for analysis, putting $t_* = T$ will yield a cross-section sample with the most variation. The stronger is the signal in the non-stationary component, the stronger is the signal of the full sample average.[4] But the presence of ϑ can magnify or suppress the fanning out effect.

To gain intuition, consider the IMA(1,1) model $\Delta x_{it} = u_{it} + \vartheta_i u_{it-1}$, where $u_{it} \sim (0, \sigma_i^2)$. It has

[4] If $\Delta x_{is,t} = g_{is} + u_{is,t}$ and thus $x_{is,t} = x_{is,0} g_{is} t + \sum_{j=1}^{t} u_{is.t-j}$, the deterministic trend dominates the stochastic trend in the averaged data, and $T^{-1}\bar{X}_{is,T} \xrightarrow{d} N(0, 1/2)$ implying that if $x_{is,t}$ is a random walk with drift, and $\text{var}_{T|is}(T^{-1}\bar{X}_{is,T}) = \frac{\sigma_{is}^2}{2}$.

$C_i(1) = 1 + \vartheta_i$, $C_i^* = -\vartheta_i$ and $w_{it} = \vartheta_i e_{it-1}$. In this model, the variance of series i at $t = T_0$ is

$$\text{var}(x_{i,T_0}) = (1 + \vartheta_i)^2 \sigma_i^2 T_0 + \vartheta_i^2 \sigma_i^2.$$

The cross-section variance at T_0 is

$$\text{var}_i(x_{i,T_0}) = \mathbb{E}_i[(1 + \vartheta_i)^2 \sigma_i^2] T_0 + \mathbb{E}_i[\vartheta_i^2 \sigma_i^2].$$

While the first term arises from dispersion in the shocks, the second term is due to parameter heterogeneity. While a positive ϑ_i increases absolute cross-section variability, a negative one decreases it. Because the effect of the innovation is quickly reversed when ϑ is negative, the fanning out of the cross-section variance is weakened as $\mathbb{E}_i[\vartheta_i]$ moves towards -1. The mean-reversion becomes extreme when $\vartheta_i = -1$ for all i since $\Delta x_{it} = \Delta e_{it}$ can be reduced to $x_{it} = e_{it}$. By implication, the fanning out effect of the stochastic trend can be significantly dampened when ϑ_i is close to -1.[5] The issue is relevant because for two plots in Figure 1, the ϑ for the U.S. series is -0.8133 and for the New York series is -0.8578.

Figure 2 plots the population-weighted cross-section variance of three measures of temperature from 1895 to 2023. The first, labeled V and plotted in black, is the cross-section variance of the temperature series itself. The second, labeled V_1 and plotted in blue, is cross-section variance in the non-stationary component based on the local-level model (ξ_{it}) estimated for each state. The third, labeled V_2 and plotted in red, is the cross-section variance of the stationary component in the local-level model. We see that while V_1 trends up starting around 1980, V_2 fluctuates around a constant mean of around 1. The timing that V_1 trends up is consistent with the reported warming in temperature in the U.S. While V is dominated by the stationary (high frequency) fluctuations in temperature, they are not strong enough to offset the underlying (low-frequency) trend. Of interest is that V_2, the cross-section variance of the non-stationary component, trends up but the cross-section variance of the stationary component does not.

The fanning out effect suggests that if we perform 'time compression' by picking one time period in a $T \times N$ panel of data for analysis, or what will subsequently be referred to as 'point sampled', the variability is maximized by selecting the last time period, T. But information in the remaining $T - 1$ periods will be ignored. The next subsection considers 'time compression' by averaging.

[5] Perron and Ng (1996) refer to this case as nearly integrated, nearly white noise.

3 Time Compression by Averaging over K Periods

Let $\bar{X}_{i,T} = \frac{1}{T}\sum_{t=1}^{T} x_{it}$ be the full sample average computed over all T observations. If x_{it} is stationary with long run variance ω_i^2, then $\sqrt{T}\bar{X}_{i,T} \xrightarrow{d} N(0,\omega_i^2)$ and $\frac{\text{var}(\bar{X}_{i,T})}{\text{var}(x_{it})} = \frac{\omega_i^2}{T\sigma_i^2}$. Time averaging of stationary data reduces noise relative to an arbitrary draw x_{it}. But if $\Delta x_{it} = u_{it}$ and $u_{it} \sim (0,\sigma_i^2)$ is stationary with long-run variance ω_i^2, then $T^{-1/2}\bar{X}_{i,T} \Rightarrow \omega_i^2 \int_0^1 W(r)d(r)$, where $W(r) \sim N(0,r)$ is a standard Brownian motion. It follows from $E[\int_0^1 W(r)dr]^2 = 1/3$ that if x_{it} is a random walk with $\sigma_i^2 = \omega_i^2$, then for large T,

$$\text{var}(\bar{X}_{i,T}) = \sigma_i^2 \frac{T}{3}.$$

In contrast to the statiionary case when the variance of $\bar{X}_{iT}$ decreases with T, the variance of $\bar{x}_{iT}$ now diverges with T. We see that the cross-section of $\bar{X}_{iT}$ also fans out with T, but not by as much as x_{iT}. The reason is that $\bar{X}_{i,K}$ is a triangular weighted sum of future shocks with more weights to the earlier periods, resulting in shrinkage factor of 1/3.

Instead of full sample averaging, consider $\bar{X}_{iK}$, an average of $K = T_1 - T_0$ observations between $T_0 + 1$ and T. Because x_{it} is a sum of past shocks, $\bar{X}_{i,K} = x_{i,T_0} + \frac{1}{K}\sum_{t=T_0+1}^{T_1}\sum_{s=T_0+1}^{t} u_{is}$. Simplifying the double sum, we to obtain

$$\bar{X}_{iK} \;=\; x_{i,T_0} + \sum_{j=1}^{K}\left(\frac{K-j+1}{K}\right)u_{i,T_0+j} = x_{i,T_0} + \sum_{j=1}^{K}\phi_j u_{i,T_0+j}.$$

With $\mathbb{E}[\bar{X}_{i,K}] = x_{i,T_0}$, $\text{var}(u_{it}) = \sigma_i^2$, and noting that $\sum_{j=1}^{K}\phi_j^2 = \frac{K(K+1)(2K+1)}{6K^2}$, we have

$$\text{var}(\bar{X}_{iK}) = T_0\omega_i^2 + a_K\omega_i^2, \qquad a_K = \frac{(K+1)(2K+1)}{6K}.$$

Lemma 1 *Suppose that $x_{it} = x_{it-1} + u_{it}$ where $u_{it} \sim (0,\sigma_i^2)$ is independent across i but possibly serially correlated with long-run variance ω_i^2, and $u_{i0} = 0$. Let $\bar{X}_{i,K}$ be the mean of unit i computed from K observations between T_0 and T_1. For fixed K, the cross-section variance is $var_i(\bar{X}_{i,K}) = (T_0 + a_k)\mathbb{E}_i[\omega_i^2]$, and for large K, $var_i(\bar{X}_{iK}) = \mathbb{E}_i[\omega_i^2]K/3$.* □

The cross-section variance has two components: one from the variance of the conditional mean, which in this case is the initial condition, and one from the mean of the conditional variance due to the shocks. We thus have $\text{var}_i(\bar{X}_{ik}) = (T_0 + a_K)\mathbb{E}_i[\omega_i^2]$ for fixed K. , Assuming T_0 is small relative to K gives a large K cross-section variance of $\mathbb{E}_i[\omega_i^2]K/3$ since $a_K \approx K/3$ for large K. If x_{it} is a random walk, $T_0 = 0$, $T_1 = T = K$, then $a_K \approx T/3$ and $\text{var}(\bar{X}_{iT}) = \mathbb{E}[\sigma_i^2]T/3$ as obtained earlier

for full sample averaging. The shrinkage factor of 1/3 still appears because averaging gives unequal weights ϕ_j to the shocks.

Lemma 1 shows that introducing serial correlation in u_{it} only changes the result from the short-run variance σ_i^2 to the long-run variance ω_i^2. Nonetheless, there can exist long-run variances that dampen the fanning out. For example, the IMA(1,1) process $x_{it} = x_{it-1} + u_{it} + \vartheta u_{it-1}$ has $\omega_i^2 = (1+\vartheta_i)^2\sigma_i^2$. The fanning effect will significantly reduced if ϑ is close to -1, which obtains when q, the signal of the I(1) relative to the I(0) component is small. This case is of interest because the local level model and common factor model that fit temperature both have an MA(1) model as reduced form. In the local-level model, the driving force of fanning out is the N individual unit-root processes each dominating the respective serially correlated noise, and hence the signal-to-noise ratio is $q_i = \sigma_u^2/\sigma_w^2$. In the factor model, we only have a single stochastic trend. The fanning out is realized only if the trend is sufficiently strong and is complemented by heterogeneity in the loadings λ_i to dominate the idiosyncratic variations. Hence, the signal-to-noise ratio for the factor model is $q_i = \sigma_u^2\sigma_\lambda^2/\sigma_w^2$.

To illustrate the fanning out of the cross-section variance, we generate data from the local level and the factor models. However, both models have a non-stationary component, and no averaging should have three times larger variance than averaged data. Both models imply that

$$R_{10} = \frac{\text{var}_i(x_{i,T_1})}{\text{var}_i(x_{i,T_0})} = \frac{T_1}{T_0}.$$

We simulate x_{ist} for $i = 1,\ldots,N, s = 1,\ldots,S$, and $t = 1,\ldots,T$ with $(T_0, T_1, T_2) = (25, 50, 150)$, $(N, S) = (50, 100)$. For the local level model, we simulate w_{ist} and u_{ist} as two independent mean-zero Gaussian errors with $\sigma_w = 1$ and $\sigma_u = (1, 0.5, 0.2, 0.1, 0)$. For the factor model, we let $\lambda_{is} \sim N(0, \sigma_\lambda^2)$, $w_{sit} \sim N(0,1)$ and $e_t \sim N(0,1)$. We set $\sigma_\lambda = (1, 0.6, 0.4, 0.2, 0)$. When $\sigma_\lambda > 0$, the model has heterogeneous loadings. When $\sigma_\lambda = 0$, we set $\lambda = 0.5$ to arrive at a factor model with a non-stationary common factor with homogeneous loadings. In each case, the signal-to-noise ratio q_i is used to compute the implied ϑ_i. In each replication, we compute the variance of x using time series data of lengths T_0, T_1, T_2, cross-section data of length N, spatial data with S units, and $S \times N$ panels of data all evaluated at the same three time points, The ratios (denoted R_{10}, R_{21} and R_{20}, respectively) are computed for T_1 relative to T_0, T_2 to T_1, and T_2 to T_0.

The top panel of Table 1 reports the ratios averaged over replications. The true variance ratios are 2, 3 and 6. Results for the local-level model are in the top panel. We see that the cross-sectional variances N, S and SN are closely in line with the results in Lemma 1 when σ_u, and hence the signal-to-noise ratio, is relatively high. This reflect the fanning out of the cross-sectional variance. When

Table 1: Variance ratios for (T_0, T_1, T_2)=(25, 50, 150), (S, N, T)=(100, 50, 150)

		T			N			S			SN		
		R_{10}	R_{21}	R_{20}	R_{10}	R_{21}	R_{20}	R_{10}	R_{21}	R_{20}	R_{10}	R_{21}	R_{20}
		2	3	6	2	3	6	2	3	6	2	3	6
σ_u	ϑ	Local level model											
1.000	-0.382	1.834	2.608	4.782	1.949	2.942	5.734	1.957	2.970	5.812	1.962	2.956	5.799
0.500	-0.610	1.524	2.218	3.381	1.858	2.828	5.254	1.855	2.861	5.309	1.863	2.847	5.303
0.200	-0.819	1.144	1.450	1.659	1.514	2.305	3.488	1.492	2.338	3.489	1.501	2.330	3.497
0.100	-0.905	1.038	1.134	1.176	1.221	1.646	2.009	1.195	1.663	1.988	1.201	1.665	2.000
0.000	-1.000	0.996	0.992	0.988	1.015	0.994	1.009	1.001	0.987	0.988	1.001	1.000	1.001
σ_λ	ϑ	Factor model											
1.000	-0.382	1.953	2.934	5.731	1.985	3.036	6.027	1.948	3.096	6.031	1.962	3.057	5.998
0.600	-0.554	1.958	2.949	5.774	1.923	2.966	5.705	1.890	3.033	5.734	1.902	2.990	5.687
0.400	-0.672	1.960	2.957	5.796	1.822	2.843	5.180	1.803	2.927	5.276	1.809	2.879	5.210
0.200	-0.819	1.963	2.964	5.818	1.517	2.378	3.607	1.574	2.582	4.063	1.567	2.524	3.956
0.000	-1.000	1.989	2.938	5.844	1.018	0.994	1.011	0.998	1.000	0.998	1.001	0.999	1.000

		SN-No averaging			SN-Centered average			SN-Partial average		
		V_0	V_1	V_2	V_0	V_1	V_2	V_0	V_1	V_2
σ_u	ϑ	Local level model								
1.000	-0.382	25.993	50.961	150.985	23.624	48.586	148.613	8.876	17.179	50.463
0.500	-0.610	7.249	13.491	38.497	5.990	12.231	37.238	2.249	4.310	12.620
0.200	-0.819	2.001	2.999	7.000	1.052	2.051	6.052	0.393	0.706	2.025
0.100	-0.905	1.252	1.500	2.500	0.346	0.596	1.597	0.128	0.192	0.511
0.000	-1.000	1.002	0.999	1.000	0.111	0.111	0.111	0.040	0.020	0.007
σ_λ	ϑ	Factor model								
1.000	-0.382	25.454	49.951	152.639	23.129	47.638	149.235	8.480	16.601	48.462
0.600	-0.554	9.803	18.620	55.592	8.397	17.221	53.797	3.079	5.989	17.450
0.400	-0.672	4.912	8.829	25.264	3.794	7.715	23.972	1.390	2.673	7.759
0.200	-0.819	1.978	2.956	7.066	1.032	2.012	6.077	0.378	0.683	1.945
0.000	-1.000	1.001	1.000	1.001	0.111	0.111	0.111	0.040	0.020	0.007

the dynamics of x is determined entirely of the dynamics of the stationary component w (i.e., $\sigma_u = 0$), the cross-sectional variance does not increase with T. Results for the factor model are given in the lower panel. Similarly to the local level model, the cross-sectional variances based on cases N, S and SN mimic these true ratios closely but in this common factor setup, the fanning out is driven by the heterogeneity of the factor loadings. When the factor loadings are homogeneous ($\sigma_\lambda = 0$), while the time-series variance (T case) is still expanding due to the non-stationarity of the common factor, the cross-sectional variance is no longer fanning out because this non-stationarity is common for all cross-sectional units.

The fanning out effect extends to $S \times N$ panels after the time dimension is collapsed. The bottom panel of Table 1 shows the average of the variances over simulations. Comparing the

variance of the averaged data and that of the raw data, the ratio is roughly 1/3. It would then seem that averaging is undesirable if the goal is to obtain data with maximum variance. The next section shows that averaging the data is desirable for estimation.

4 Estimation of Long-Run Relations by Cross-Section Regressions

In this section, we analyze the implications of using time averaged data for regressions. The first subsection analyzes the case when x_{it} is I(1). The I(0) case is analyzed in the second subsection.

4.1 Non-Stationary x

We consider a setting in which x_{it} is non-stationary, and y_{it} depends on x_{it} and possibly lags of y_{it} and x_{it}. We start with the static case:

$$x_{it} = x_{it-1} + u_{it} \tag{1a}$$

$$y_{it} = \beta x_{it} + e_{it}, \tag{1b}$$

where $u_{it} \sim (0, \sigma_i^2)$ and $e_{it} \sim (0, \tau_i^2)$. Since x_{it} is I(1) and e_{it} is stationary by assumption, β characterizes the stable, low frequency relation bewteen y and x, and $(1, -\beta)$ is a cointegrating vector. We know that a regression of using $T \times N$ panel data of y and x, or a time series regression using T observations of y and x of a particular unit will converge at the fast rate of T. While this super consistent rate gives precise estimates, the asymptotic distribution of $\hat{\beta}$ is, in general, non-standard. Instead, we consider a 'timeless' cross-section regression.

To motivate, consider a projection of $\bar{Y}_{iK}$ on $\bar{X}_{iK}$. The 'bias' from the projection is

$$\text{bias} = \frac{\text{cov}_i(\bar{X}_{iK}, \bar{e}_{iK})}{\text{var}_i(\bar{X}_{iK})}.$$

From the preceding analysis, $\bar{X}_{iK} = O(K^{1/2})$ because time averaging allows $\bar{X}_{iT}$ to be increasingly dominated by accumulated permanent shocks. If $e_{it} \sim (0, \tau_i^2)$, then $\bar{e}_{iK} = O(K^{-1/2})$. Because the signal in $\bar{X}_i$ grows while the noise $\bar{e}_{iK}$ decreases with K, the bias vanish with K.

The (cross-section) between-group regression is

$$\bar{Y}_{iK} = c + \beta \bar{X}_{iK} + \bar{e}_{ik}. \tag{S}$$

Assumption A: (a) $u_{is} \perp e_{it}$ for all s, t and for all i; (b) $(\bar{X}_{iK}, \bar{e}_{iK})$ are i.i.d. across i with finite fourth moments, and (c). $\mathbb{E}_i[\sigma_i^2] > 0$.

We assume that u_{is} and e_{it} are independent across i and t. With temperature as x in mind, the strict exogeneity assumption is not restrictive. Assumption A.(c) is needed for the asymptotic variance to be non-degenerate.

Under Assumption A, we study the sampling properties of the least squares estimator

$$(\hat{\beta} - \beta) \quad = \quad \frac{\sum_{i=1}^{N} (\bar{X}_{iK} - \bar{X}_K)\bar{e}_{iK}}{\sum_i (\bar{X}_{iK} - \bar{X}_K)^2}.$$

Proposition 1 *For $i = 1, \dots N$ and $t = 1, \dots T$, let the data be generated by (1a) and (1b). For each i, let $(\bar{X}_{iK}, \bar{Y}_{iK}, \bar{e}_{iK})$ be the average of (y_{it}, x_{it}, e_{it}) between $t = T_0 + 1$ and T_1. Then, under Assumption A,*

- *As $N \to \infty$ with K fixed, $\sqrt{N}(\hat{\beta} - \beta) \xrightarrow{d} \mathcal{N}(0,\ Q_{XX}^{-1} V_K Q_{XX})$, where $a_K = \frac{(K+1)(2K+1)}{6K}$, $V_K = \mathbb{E}_i[(\bar{X}_{iK} - \mu_X)^2 \bar{e}_{iK}]$ and $Q_{XX} = var_i(\bar{X}_{iK}) = (T_0 + a_K)\mathbb{E}_i[\sigma_i^2]$.*
- *For large K, $\sqrt{N}K(\hat{\beta} - \beta) \xrightarrow{d} \mathcal{N}(0, \mathcal{Q}_{XX}^{-1} \mathcal{V} \mathcal{Q}_{XX}^{-1})$ where $\mathcal{Q}_{XX} = \lim_{K\to\infty} K^{-1} Q_{XX}$, and $\mathcal{V} = \lim_{K\to\infty} V_K$.*

The proof is given in the Appendix. In the fixed K case, the variability in initial condition $\bar{x}_{i,T0}$ matters. The variance of $\sqrt{N}(\hat{\beta} - \beta)$ thus tends to zero at rate K^2. This is because the numerator of $\hat{\beta} - \beta$ is a sum of $O(1)$ terms, while the denominator is a sum of $O(K^2)$ terms. For this model, $\mathcal{V} = \mathbb{E}_i[\sigma_i^2 \tau_i^2]/3$, $\mathcal{Q}_{XX} = \mathbb{E}[\sigma_i^2]/3$, and $\mathcal{Q}_{XX}^{-1} \mathcal{V} \mathcal{Q}_{XX}^{-1} = \frac{3\mathbb{E}_i[\sigma_i^2 \tau_i^2]}{(\mathbb{E}_i[\sigma_i^2])^2})$ for all $K > 1$. For large K, terms related to x_{iT_0} vanish. The cross-section 'between' estimator is super-consistent in the sense that the rate is faster than the usual rate of $\sqrt{N}$. Intuitively, the variation in $\bar{X}_{iK}$ accumulates as K grows while that of $\bar{e}_{iK}$ shrinks, so that $\text{var}_i(\bar{X}_{iK}) = O(K)$ but $\text{var}_i(\bar{e}_{iK}) = O(K^{-1})$. If u_{it} and e_{it} have homogeneous variance, $\sqrt{N}K(\hat{\beta} - \beta) \sim (0, 3\tau_i^2/\sigma_u^2)$. Of note is that the estimator is asymptotically normal. Proposition 1 implies that the most efficient cross-section regression is to perform full sample averaging. With $K = T$, $\hat{\beta}$ is $\sqrt{NT}$ consistent and asymptotically normal despite the fact that x_{it} is I(1) and we are performing a cross-section regression. If $K = 1$, we obtain the standard cross-section result that $\sqrt{N}(\hat{\beta} - \beta) \xrightarrow{d} N(0, \frac{\mathbb{E}_i[x_{i,T_0} \tau_i^2]}{(\mathbb{E}_i[x_{i,T_0+1}^2]^2)})$.

Proposition 1 assumes that the static regression (S) correctly specifies the simple data generating

process. Now suppose that x_{it} continues to be a random walk as given in (1a), but now let

$$y_{it} = \alpha y_{it-1} + \beta_0 x_{it} + \beta_1 x_{it-1} + e_{it}, \qquad e_{it} \sim (0, \tau_i^2). \tag{2b}$$

Following Bewley (1979), (2b) can be rearranged as

$$\begin{aligned}(1-\alpha)y_{it} &= -\alpha\Delta y_{it} + (\beta_0+\beta_1)x_{it} - \beta_1\Delta x_{it-1} + e_{it} \\ y_{it} &= \left(\frac{\beta_0+\beta_1}{1-\alpha}\right)x_{it} - \underbrace{\alpha^*\Delta y_{it} + \beta_1^*\Delta x_{it-1}}_{\eta_{it}} + e_{it}^*,\end{aligned}$$

where $\alpha^* = \alpha/(1-\alpha), \beta_1^* = \beta_1/(1-\alpha)$ and $e_{it}^* = e_{it}/(1-\alpha)$. The quantity

$$\theta^\dagger = \frac{\beta_0+\beta_1}{1-\alpha}$$

is often referred to as the long-run multiplier (LRM). A regression of y on x omits $\Delta y_{it}, \Delta x_{it-1}$ and $\mathbb{E}_i[\eta_{it}x_{it}] \neq 0$. Thus if x_{it} were stationary, a time series or a panel regression would yield inconsistent estimates. If x_{it} is I(1), a time series regression would yield super consistent estimates which converge at rate T because the omitted variable bias is of second order but the distribution of $\hat{\beta}$ is non-standard. Now in terms of time averaged data,

$$\bar{Y}_{iK} = \theta^\dagger \bar{X}_{iK} - \eta_{iK} + \frac{\bar{e}_{iK}}{1-\alpha}.$$

What would a least squares regression of $\bar{Y}_{iK}$ on $\bar{X}_{iK}$ yield?

Proposition 2 *Suppose that x_{it} is I(1), y_{it} is generated by the dynamic model given in (2b) with $|\alpha| < 1$, and Assumption A holds. Consider least squares estimation of the static regression (S) using $\bar{Y}_{iK}$ and $\bar{X}_{iK}$.*

i As $N \to \infty$ with K fixed, $\sqrt{N}\left(\hat{\beta} - \theta^\dagger + \frac{cov_i(\bar{X}_{iK},\eta_{iK})}{var_i(\bar{X}_{iK})}\right) \xrightarrow{d} N(0, Q_{XX}^{-1}W_K Q_{XX}^{-1})$ where $W_K = var_i((\bar{X}_{iK} - \mu_X)(\bar{e}_{iK}\eta_{iK}))$ and $Q_{XX} = var_i(X_{iK})$.

ii For large K, $\sqrt{N}K(\hat{\beta} - \theta^\dagger) \xrightarrow{d} N(0, \mathcal{Q}_{XX}^{-1}\mathcal{W}\mathcal{Q}_{XX}^{-1})$, where $\mathcal{W} = \lim_{K\to\infty} KW_K$.

The omitted lags collected into η_{iK} in the time averaged regression are of the same order as the I(0) regressors. The omitted variable bias is $\frac{\mathrm{cov}_i(\bar{X}_{iK}, \bar{e}_{iK}^* - \eta_{iK})}{\mathrm{var}_i(\bar{X}_{iK})}$ for fixed K. Since $\bar{X}_{iK}$ only depends on $\{u_{it}\}$ and $u_{it} \perp e_{is}$ by assumption, we only need to consider $\mathrm{cov}_i(\bar{X}_{iK}, \eta_{iK})$. As $\bar{X}_{iK} = O_p(K^{1/2})$ and $\eta_{iK} = O_p(K^{-1/2})$, their product is $O(1)$ and upon scaling by $\mathrm{var}(\bar{X}_{iK})$, we have a bias that is $O_p(K^{-1})$ that vanishes with K. We thus have a $\sqrt{N}K$ consistent estimate of the long-run multiplier

as K increases. Though $\bar{e}^*_{iK}$ does not contribute to the bias, it affects the variance as is indicated in W_K. Because $e^*_{it} = \frac{e_{it}}{1-\alpha}$ and $\alpha < 1$, $\text{var}(\bar{e}_{iK}) > \text{var}(\bar{e}_{iK})$.

The preceding analysis assumes that $T \times N$ panels of y and x are available. Suppose we have data $(x_{is,t}, y_{is,t})$ for $i = 1, \dots N$ units in each location $s = 1, \dots S$ for $t = 1, \dots T$, a panel fixed effect regression

$$\bar{Y}_{is,K} = \beta X_{is,K} + \delta_i + \zeta_s + \bar{\mathcal{E}}_{iK}$$

will result in $\sqrt{NS}K(\hat{\beta} - \beta) \xrightarrow{d} N(0, \mathcal{V})$ as $N, S \to \infty$. Effectively, we have a regression in NS observations of centered data $\widetilde{X}_{is} = \bar{X}_{is} - \bar{X}_{i.} - \bar{X}_{.s} + \bar{X}_{..}$, and $\widetilde{Y}_{is}$ is similarly defined.

4.2 Stationary x

The above subsection shows that time averaging data over K-periods yield $\sqrt{N}K$ consistent estimates of the estimand in the static regression, which can be β or θ depending on the model for y_{it}. When x_{it} is stationary, $(1, -\beta)$ no longer bears the interpretation of a cointegrating vector. So what does a regression of y on x estimate? In this sub-section, we assume that

$$x_{it} = \rho x_{it-1} + u_{it}, \quad u_{it} \sim (0, \sigma_i^2), \tag{1b}$$

where $|\rho_i| < 1$, u_{it} has long-run variance

$$\omega_i^2 = \frac{\sigma_i^2}{(1-\rho_i)^2} > 0.$$

Recall that in the I(1) case, $\bar{X}_{iK} = O_p(K^{1/2})$. In the present I(0) case, $\bar{X}_{iK} = O_p(K^{-1/2})$. We start with estimation of the static model (S).

Proposition 3 *Suppose that x_{it} is generated as in (1b) with $|\rho| < 1$ and Assumption A holds. Consider least squares estimation of the static model (S).*

- *If y_t is generated by (1b) with $|\alpha| < 1$, then for all K, $\sqrt{N}(\hat{\beta} - \beta) \xrightarrow{d} N(0, Q_{XX}^{-1} V_K Q_{XX}^{-1})$ where $V_K = var_i((\bar{X}_{iK} - \mu_X)\bar{e}_{iK})$ and with $Q_{XX} = var_i(\bar{X}_{iK})$.*
- *If y_{it} is generated by (2b), then $\sqrt{N}\left(\hat{\beta} - \theta^\dagger + \frac{cov_i(\bar{X}_{iK}, \eta_{iK})}{var_i(\bar{X}_{iK})}\right) \xrightarrow{d} N(0, Q_{XX}^{-1} W_K Q_{XX}^{-1})$ with K fixed, where $W_K = var_i((\bar{X}_{iK} - \mu_X)(\bar{e}_{iK} - \eta_{iK}))$. For large K, $\sqrt{N}(\hat{\beta} - \theta^\dagger) \xrightarrow{d} N(0, \mathcal{Q}_{XX}^{-1} \mathcal{W} \mathcal{Q}_{XX}^{-1})$.*

Proposition 3 has two parts, both requiring $\mathbb{E}_i[\omega_i^2] > 0$ for identification because $Q_{XX} = \mathbb{E}_i(\omega_i^2)/K$. Variability can come from heterogeneity in ρ_i or σ_i^2, or both. With homoskedastic errors, there is no cross-sectional variation from heterogeneous means, and the sandwich degenerates. When this is ruled out in both cases, $Q_{XX} = O(K^{-1})$ while V_K and W_K are $O(K^{-2})$. The variance is finite for every K and the asymptotic distributions are valid for all K.

In part (i), the model for y_{it} coincides with the regression model. Then, the estimator is unbiased at any K and is $\sqrt{N}$ consistent. Averaging now reduces both the signal $\text{var}(\bar{X}_{iK})$ and the noise V_K at the same rate of $1/K$. As a consequence, we no longer achieve the super-consistent rate that is obtained when x_{it} is I(1). Since the asymptotic distribution also holds when $K = 1$, this means that a single cross-section regression using the data sliced at $T_0 + 1$ will have the same precision as averaging over many periods. It should be noted, however, that $\bar{X}_{iK} \approx \omega_i^2/K$ and hence the persistence of x_{it} also affects the precision of $\hat{\beta}$.

In part (ii) when the static regression is misspecified, the estimator is biased for the long-run multiplier when K is fixed. Now $\eta_{iK} = O_p(K^{-1})$ which tends to zero faster than in the I(1) case when $\eta_{iK} = O_p(K^{-1/2})$. Nonetheless, the bias shrinks slower than in the I(1) case. This is because $\text{var}(\bar{X}_{iK})$ is $O(K^{-1/2})$ when x is I(0) compared to $O(K^{-1})$ when x is the I(1). Since $\text{cov}_i(\bar{X}_{iK}, \eta_{iK}) = O(K^{-1/2})O(K^{-1})$, the bias of $O_p(K^{-1/2})$ is larger than in the I(1) case, but nonetheless tends to zero as K increases.

It has been suggested in the literature that averaging the data over many periods allows us to estimate the medium and longer term effects. Our analysis shows that K affects the asymptotic properties of the estimator, but the estimand is always the long-run multiplier as defined in the textbook; it has no 'medium' or 'longer term' interpretation. In summary, when y_{it} is generated by (2b), whether x is I(1) or I(0), the cross-section estimator of $\theta^\dagger$ is biased when K is fixed, but is consistent and asymptotically normal as K increases. However, $\hat{\theta}^\dagger$ is super-consistent only when x is I(1). Quantities other than the long-run multiplier can be used to characterize the dynamic effects of changes in x, or of shocks to x, but for that, we will need to estimate a dynamic model.

4.3 Short-Run Effects and Cross-Section Regressions of Dynamic Models

We now suppose that y_{it} is generated as in (2b) and incorporate the lagged variables. When x is I(1), x_{it} will be highly collinear with $x_{i,t-1}$. Thus, we reparameterize model (2b) as6

$$\begin{aligned} y_{it} &= \alpha y_{it-1} + \beta_0 x_{it} \beta_1 x_{it-1} + e_{it} \\ y_{it} &= \alpha y_{it-1} + (\beta_0 + \beta_1) x_{it} - \beta_1 \Delta x_{it-1} + e_{it} \\ &= \alpha y_{it-1} + \delta_0 x_{it} + \delta_1 \Delta x_{it-1} + e_{it}. \end{aligned}$$

The parameter β_0 in the original model (2b) is the short-run (impact) effect and β_1 is the lagged effet. In the reparametrized model, we can identify the sum of the current and lagged effects as given by δ_0, and the lagged effect, as given by β_1. Or, we can reparameterize the model as $y_{it} = \alpha y_{it-1} + \beta_0 \Delta x_{it} + (\beta_0 + \beta_1) x_{it-1} + e_{it}$ to identify $\delta_0 = (\beta_0 + \beta_1)$ and β_0. But with collinearity between x_{it} and x_{it-1}, the short-run parameters β_0 and β_1 cannot be jointly identified. Whichever reparameterized model we estimate, x_{it} is generated by u_{it} which is uncorrelated with e_{it} by assumption, so bias can only arise from correlation between $y_{i,t-1}$ and e_{it}. In standard dynamic panel regressions, $\text{cov}(y_{i,t-1} - \bar{y}_{i,-1}, e_{it} - \bar{e}_i) = O(T^{-1})$. As $\text{var}(y_{i,t-1} - \bar{y}_{i,-1}) = O(1)$, Nickell bias is $O(T^{-1})$.

Cross-section regressions involve data without a time dimension, but it can still be used to estimate dynamic models. In particular, we want to perform a between-group dynamic regression in time-aggregated data

$$\begin{aligned} \bar{Y}_{iK} &= c + \alpha \bar{Y}_{iK,-1} + \beta_0 \bar{X}_{iK} + \beta_1 \bar{X}_{iK} + \bar{e}_{iK} \\ &= c + \alpha \bar{Y}_{iK,-1} + \delta_0 \bar{X}_{iK} + \delta_1 \Delta \bar{X}_{i,K} + \bar{e}_{iK} \\ &= c + \alpha \bar{Y}_{iK,-1} + \delta_0 \bar{X}_{iK} + \delta_1 \frac{(x_{i,T_1} - x_{i_{T_0}})}{K} + \bar{e}_{iK}. \end{aligned} \tag{3b}$$

The relevant term for Nickell bias is

$$NB = \frac{\text{cov}(\bar{Y}_{iK,-1} e_{ik})}{\text{var}_i(\bar{Y}_{iK,-1})}.$$

Since the numerator is $O(K^{-1})$, regardless of whether x is I(1) or I(0), the difference is in the denominator. In particular, $\text{var}_i(\bar{Y}_{iK,-1}) = O(K)$ in the I(1) case and $\text{var}(\bar{Y}_{iK,-1}) = O(K^{-1})$ in the I(0) case. We need to consider them separately.

Proposition 4 *Suppose y_{it} is generated as in (2b) and Assumption A holds.*

i *If* x_{it} *is* $I(1)$, *var*$(\bar{Y}_{iK}) = O(K)$ *so that NB=*$O(K^{-2})$. *Let* $Z_{iK} = (\bar{Y}_{iK,-1}, \bar{X}_{iK}, \Delta x_i)'$, $B_1 = (\alpha, \delta_0, \delta_1)'$ *and* $D_K = diag(K, K, K^{-1})$. *Then, estimation of (3b) yields*

$$\sqrt{N} D_K(\hat{B}_1 - B_1) \xrightarrow{d} N(0, \mathcal{Q}_{ZZ}^{-1} \mathcal{V}_1 \mathcal{Q}_{ZZ}^{-1})),$$

where $\mathcal{Q}_{ZZ} = \lim_{K\to\infty} D_K^{-1} Q_{ZZ} D_K^{-1}$ *with* $Q_{ZZ} = var_i(\bar{Z}_{iK})$ *and* $\mathcal{V}_1 = \lim_{K\to\infty} D_K^{-1} V_{1K} D_K^{-1}$, $V_{1K} = var_i(\bar{Z}_{iK}\bar{e}_{iK})$.

ii. *If* x_{it} *is generated by (1b) and* $\omega_i^2 = \sigma_i^2/(1-\rho_i)^2 > 0$, *then* $var_i(\bar{Y}_{iK}) = O(K^{-1})$ *and NB=*$O(1)$. *Let* $Z_{iK} = (\bar{X}_{iK}, X_{ik,-1})'$ *and* $B_0 = (\beta_0, \beta_1)'$. *Least squares estimation of (3b) yields*

$$\sqrt{N}(\hat{B}_0 - B_0) \xrightarrow{d} N(0, \widetilde{\mathcal{Q}}_{ZZ}^{-1} \widetilde{\mathcal{V}}_0 \widetilde{\mathcal{Q}}_{ZZ}^{-1}),$$

where $\widetilde{Z}_{iK}$ *projects out* Y_{iK} *from* Z_{iK}, $\mathcal{Q}_{\widetilde{Z}\widetilde{Z}} = \lim_{K\to\infty} Q_{\widetilde{Z}\widetilde{Z}}/K$ *with* $Q_{\widetilde{Z}\widetilde{Z}} = var_i(\widetilde{Z}_{iK})$ *and* $\mathcal{V} = \lim_{K\to\infty} \widetilde{V}_{0K}/K^2$, $\widetilde{V}_{0K} = var_i(\widetilde{Z}_{iK}\widetilde{e}_{iK})$.

Proposition 4 states that the bias in $\hat{\alpha}$ from least squares estimation vanishes as K increases in the I(1) case but not in the I(0) case. Although the numerator is the same in both cases, the signal var$(\bar{Y}_{iK})$ grows with K and overwhelms the noise in the I(1) case but not in the I(0) case. Though the estimates in the I(1) case are consistent, we have two non-stationary regressors $(\bar{Y}_{iK}, \bar{X}_{iK})$ and one stationary regressor $\Delta x_i = \frac{x_{i,T_1} - x_{i,T_0}}{K}$. The three estimates in $\hat{B}$ converge at different rates, with $\hat{\alpha}$ and $\hat{\delta}_0$ being $\sqrt{N}K$ consistent and $\hat{\delta}_1$ being $\sqrt{N}$ consistent. The result is analogous to Sims et al. (1990) that in a time series regression, coefficients on the I(1) variables converge at a faster rate than the coefficinets on the I(0) variables.

If x_{it} is $I(0)$, y_{it} is also stationary, so that the Nickell bias is now $O(1)$ and $\hat{\alpha}$ is not consistent, nor can a bias-correction be made. Recall that the standard within-estimator has cov$(\ddot{y}_{it}, \dot{e}_{it})$ is $O(T^{-1})$. In the present setting,

$$\text{cov}(\bar{Y}_{iK,-1}, \bar{e}_{iK}) = \frac{\tau_i^2}{K^2(1-\alpha)}\left[K - \frac{1-\alpha^K}{1-\alpha}\right].$$

Averaging dilutes the covariance from K to T but does not eliminate it. If $K = T$ as in the case of full sample averaging, the covariance would be the same order as the within estimator. But while the denominator $var(\ddot{y}_{i,t-1}) = O(1)$ in within estimation to give a Nickell bias is $O(T^{-1})$, the denominator is also $O(K^{-1})$ giving a bias of $O(1)$ in the present setting, It is nonetheless useful to remark that cov$(\bar{Y}_{i,K-1}, \bar{e}_{iK})$ is zero when $K = 1$ and increases with K. The Nickell bias might not be severe in the I(0) case.

In spite of the bias in $\hat{\alpha}$, we can consistently estimate β_0 and β_1 with a rate of $\sqrt{N}$ when x is I(0). It is interesting that in this stationary case, estimation of the static model, though misspecified, would consistently estimate the long-run multiplier, θ. Yet, when we correctly specify the model, we can only estimate two of the three parameters. This is because in the static regression, $\bar{X}_{iK}$ is the only regressor and it is exogenous, but in the dynamic model, $\bar{Y}_{iK}$ is an endogeneous regressor correlated with the error. While simple averaging cannot eliminate Nickel bias, observe that it is zero when x is I(1). This implies that if we also specify a process x_{it}, computing impulse responses from the parameter estimates will not be an issue when x is I(1), but can be an issue when x is I(0) because coefficients on the lagged dependent variable will be biased. We will explore this in simulations.

Putting the results of the I(1) and I(0) case together, cross-section estimation of a static or a dynamic model can be consistent for the corresponding the long- and short-run effects of x_t without knowing a priori whether x is I(1) or I(0), and the estimates will be asymptotically normal.

5 A Class of Time Compression Functions

The above analysis uses time averaging to collapse the time variation, but other time compression schemes are possible. We now let $\widetilde{X}_{iK} = \sum_{t=T_0}^{T_1} w(t) x_{it}$ for some time compression function $w(t)$. K period averaging puts $w(t) = 1/K$ for $t \in [T_0 + 1, T_1]$ while point sampling at $t = T_1$ puts $w(t) = 1$ at $t = T_1$ and zero others. Other weighting schemes are possible.

In the I(1) case, $x_{it} = x_{it-1} + u_{it}$. Since $x_{it} = x_{i0} + \sum_{s=T_0+1}^{t} u_{is}$, we change the order of summation, so we can sum over s first, and then for $t > s$ we obtain

$$\begin{aligned} \widetilde{X}_{iK} &= x_{i,T_0} + \left(\sum_{t=T_0+1}^{T_1} w(t) \sum_{s=T_0+1}^{t} u_{is} \right) = x_{i,T_0} + \sum_{s=T_0+1}^{T_1} u_{is} \sum_{t=s}^{T_1} w(t) \\ &= x_{i,T_0} + \sum_{s=T_0+1}^{T_1} \phi_s u_{is}, \qquad \text{with} \qquad \phi_s = \sum_{t=s}^{T_1} w(t), \end{aligned}$$

where ϕ_s is the sum of the total weight placed on periods at or after s. The sequence $\{\phi_s\}$ is thus the survival function of the weight distribution w, starting at $\phi_{T_0+1} = \sum_{t=T_0+1}^{T_1} w(t) = 1$ to $\phi_{T_1} = \widetilde{w}(T_1)$. The time compressed variable $\widetilde{X}_{iK}$ depends on the initial condition and the shocks, its variability $\text{var}(\widetilde{X}_{iK}) = \sigma_i^2 \Phi_K$ is dominated by Φ_K, shown in the Appendix to be $O(K)$. We

thus have

$$\Phi_K = \sum_{s=T_0+1}^{T_1} \phi_s^2 = \widetilde{a}_K K,$$

where $\widetilde{a}_K$ depends on the time compression scheme. For K period averaging, $\widetilde{a}_K = 1/3$, and for point sampling, $\widetilde{a}_K = 1$.

In the stationary case, we have, by definition,

$$\text{var}(\widetilde{X}_{iK}) = \sum_{s=T_0+1}^{T_1} \sum_{t=T_0+1}^{T_1} w(t)w(s)\text{cov}(x_{it}, x_{is}).$$

Consider $x_{it} = \rho x_{i,t-1} + u_{it} = \sum_{s=0}^{\infty} \rho_i^s u_{t-s}$ where $u_{it} \sim (0, \sigma_i^2)$, we have $\bar{X}_{iK} = \sum_{s=T_0+1}^{T_1} \psi_s(\rho_i) u_{is}$ with $\psi_s(\rho_i) = \sum_{t=s}^{T_1} w(t)\rho_i^{t-s}$ and $\text{cov}(x_{it}, x_{is}) = \frac{\sigma_i^2}{1-\rho_i^2}\rho_i^{|t-s|}$. Thus

$$\text{var}(\widetilde{X}_{iK}) = \frac{\sigma_i^2}{1-\rho_i^2} \sum_{h=-(K-1)}^{(K-1)} \sum_{t-s=h} w(t)w(s)\rho_i^{|t-s|} \equiv \frac{\sigma_i^2}{1-\rho_i^2} G(\rho) \equiv \sigma_i^2 \Psi_K(\rho).$$

The function $\psi_s(\rho_i)$ plays the role of ϕ_s in the unit root case. With K period averaging, it is immediate that from the variance of the mean of a covariance stationary process that $\Psi_K(\rho) = O(K^{-1})$. We show in the Appendix shows that $\Psi_K(\rho) = O(K^{-1})$ for other $w(t)$ that are spread out over K periods, and is $O(1)$ when $w(t)$ is concentrated in one period.

Now our earlier analysis shows that $\hat{\beta}$ estimated from the (correctly specified) static model has a normal asymptotic distribution whether x is I(1) or I(0), albeit with different convergence rate. This is a consequence of the fact that $\text{var}(\widetilde{X}_{iK}) = \sigma_i^2 \Phi_K = O(K)$ when x is I(1), but $\text{var}(\widetilde{X}_{iK}) = \sigma_i^2 \Psi_K = O(K^{-1})$ when x is I(0). For the asymptotic distribution to evolve smoothly from I(1) to I(0), it must be the case that Ψ_K behaves like Φ_K when x is highly persistent. Indeed, we show in the Appendix that $0 \leq G(\rho_i) \leq 1$ for any $\rho_i \in [0, 1]$ and any $w(t)$. This implies that Φ_K scales with K via $\frac{\sigma_i^2}{1-\rho_i^2}$. In the local-to-unity case when $\rho_i = 1 - \frac{c_i}{K}$, $\frac{1}{1-\rho_i^2} = \frac{1}{(1-\rho_i)(1+\rho_i)} \propto \frac{K}{2c_i}$. If $\rho_i = 1 - \frac{c_i}{K^d}$, $\frac{1}{1-\rho_i} \propto \frac{c_i}{K^d}$. This allows $\text{var}(\bar{X}_i)$ to transition smoothly from $O(K^{-1})$ (stationary) to $O(1)$ (unit root).

Theorem 1 *Let x_{it} be $I(d)$ for $d = 0$ or 1 and define $\bar{X}_{iK} = \sum_{t=T_0+1}^{T_1} w(t)x_{it}$ where $w(t)$ is a time compression function satisfying (i) $w(t) \geq 0$ for all t and (ii) $\sum_{t=T_0+1}^{T_1} w(t) = 1$. Then,*

a. $\psi_s(\rho_i) \xrightarrow{\rho_i \to 0} w(s)$ *and* $\psi_s(\rho_i) \xrightarrow{\rho_i \to 1} \phi_s$*;*

b. $\Psi_K(\rho_i) \to \sum_t w(t)^2 = O(K^{-1})$ *as* $\rho_i \to 0$ *and* $\Psi_K(\rho_i) \to \Phi_K = O(K)$ *as* $\rho \to 1$.

Let $y_{it} = \beta x_{it} + e_{it}$ *with* $u_{it} \perp e_{is}$ *for all* s, t *and for all* i. *Suppose that (iii)* $Q_{XX} = var_i(x_{i,T_0}) + \mathbb{E}_i[\sigma_i^2]\Phi_K > 0$ *and (iv)* $\Phi = \lim_{K\to\infty} \Phi/K > 0$. *Let* $\widetilde{\beta}$ *be estimated from time compressed data. Under Assumptions (i)-(iv),*

c. $\widetilde{\beta} \xrightarrow{p} \beta$ *as* $N \to \infty$ *for any* K *regardless of whether* x_{it} *is I(1) or I(0);*

d. $\sqrt{N}K^d(\widetilde{\beta} - \beta) \xrightarrow{d} N(0, Q_{XX}^{-1} V_K Q_{XX}^{-1})$ *for any* K.

The two conditions on $w(t)$ ensure that it is a proper probability distribution over the interval $[T_0 + 1, T_1]$. Part (a) says that the tail sum ϕ_s interpolates continuously between the two extremes. Part (b) indicates that Ψ_K also has a smooth transition from $O(K^{-1})$ as ρ_i moves from ρ_i values of mild persistence to $O(K)$ when $\rho_i = 1$. Condition (iii) is a rank condition for identification, and (iv) ensures that enough I(1) signals are accumulated in the compressed data. If the data point sampled in an early period, say, $t = T_0$ with $\phi_s = 1_{s=T_0+1}$. Then $\Phi_K = 1$ and the condition fails because $\lim_{K\to\infty} \Phi_K/K = 0$.

Under conditions (i)-(iv), the fanning out of cross-section variance permits consistent estimation of parameters in a correctly specified model as $\text{var}_i(\widetilde{X}_{iK})$ is Q_{XX} which scales the asymptotic variance. The convergence rate of $\widetilde{\beta}$ of $\sqrt{N}K^d$ depends d, the degree of integration of x_{it}. Thus when x is I(1), $\widetilde{\beta}$ has the properties given in Proposition 1 with a_K replaced by $\widetilde{a}_K$ of the associated $w(t)$, and has the same properties as given in part (i) of Proposition 3 when x is I(0).

The above fixed K results assume that the static model is correctly specified. Though the static model is misspecified when the DGP is dynamic, the long-run multiplier is still $\sqrt{N}K$ consistent and asymptotically normal as shown in Proposition 2 for the I(1) case, and $\sqrt{N}$ consistent and asymptotically normal as in Proposition 3 for the I(0) case, and the asymptotic distribution moves smoothly between the two cases. Though Nickell bias does not vanish in the I(0) case even when K is large, the estimates of a distributed lag model without the autoregressive part are unbiased.

5.1 Relaxing Strict Exogeneity

The result that θ can be estimated from a misspecified static model suggests, as in time series regressions with I(1) regressors, endogeneity bias may also be of second order when K is large. We now make this result precise.

Consider again $y_{it} = \beta x_{it} + e_{it}$, where $u_{is} \perp e_{it}$ for all i, s, t, $(\widetilde{X}_{iK}, \widetilde{e}_{iK})$ are iid over i with finite fourth moments. Let $\widetilde{\beta}$ be obtained from the cross-section regression $\widetilde{Y}_{iK} = c + \beta \widetilde{X}_{iK} + \widetilde{e}_{iK}$ using time compressed data $(\widetilde{Y}_{iK}, \widetilde{X}_{iK})$. Under strict exogeneity, $\text{cov}_i(\widetilde{X}_{iK}, \widetilde{e}_{iK}) = \sum_s \phi_s \sum_t w(t)\mathbb{E}_i[u_{it}e_{is}] = 0$. We now allow a correlation coefficient γ_{ih} when e_{is} and u_{it} are separated $h = s - t$ periods apart:

$$\text{cor}(u_{it}, e_{is}) = \gamma_{i,t-s}, \qquad \text{or} \qquad \text{cov}(u_{it}, e_{is}) = \gamma_{i,t-s}\sigma_i\tau_i.$$

We assume that $\sum_h |\gamma_{i,h}| \leq \infty$. From $\bar{X}_{iK} = x_{i,T_0} + \sum_s \phi_s u_{is}$ and $\bar{e}_{iK} = \sum_t w(t)e_{it}$ for $s, t \in [T_0 + 1, T_1]$, we have

$$\begin{aligned} \text{cov}(\bar{X}_{iK}, \bar{e}_{iK}) &= \text{cov}\left(x_{i,T_0} + \sum_s \phi_s u_{is},\ \sum_t w(t)e_{it} \right) \\ &= \sigma_i\tau_i \sum_s \sum_t \phi_s w(t)\gamma_{i,s-t}. \end{aligned}$$

Note first that $\sum_s \sum_t \gamma_{i,s-t} \xrightarrow{p} \sum_{j=-\infty}^{\infty} \gamma_j = \Gamma$ is the long-run cross-covariance. With K-averaging when $w(t) = 1/K$ and $\phi_s = \frac{(T_1 - s + 1)}{K}$, grouping by lag $h = s - t \geq 0$,

$$\sum_{s-t=h} \phi_s w(t) = \frac{1}{K} \sum_{\substack{s-t=h \\ T_0+1 \leq s,t \leq T_1}} \frac{T_1 - s + 1}{K} = \frac{1}{K} \sum_{j=h+1}^{K} \frac{(K - j + 1)}{K} \to \frac{1}{2} = b_K.$$

A similar result holds for $h < 0$. The b_K plays the role of a_K in the earlier analysis for $\text{var}(\bar{X}_{iK})$ to yield $\text{cov}(\widetilde{X}_{iK}, \widetilde{e}_{iK}) = \sigma_i\tau_i\Gamma_i/2$. Thus

$$\mathbb{E}_i\text{cov}(\widetilde{X}_{iK}, \widetilde{e}_{iK}] = \mathbb{E}_i[\sigma_i\tau_i\Gamma_i/2] = O(1).$$

Although the covariance due to endogeneity is $O(1)$, $\text{var}_i(\widetilde{X}_{iK}) = \widetilde{a}_K \mathbb{E}_i[\sigma_i^2]$, and for K period averaging, $\widetilde{a}_K = K/3$. Thus, endogeneity bias is $O(K^{-1})$, same as the bias when the long-run multipler is estimated from the misspecified static model, and both biases vanish as K increases.

Endogeneity may arise in some other forms, but the idea is the same. For example, consider

$$\begin{aligned} x_{it} &= x_{it-1} + \kappa y_{it-1} + u_{it} \\ y_{it} &= \beta_0 x_{it} + \beta_1 x_{it-1} + e_{it}. \end{aligned}$$

Then $x_{it} = (1 + \kappa\beta_0)x_{it-1} + \kappa\beta_1 x_{it-2} + \kappa e_{it-1} + u_{it}$ is still nearly I(1) if $|\kappa(\beta_0 + \beta_1)|$ is small. The effective innovation is now $u_{it}^* = \kappa_1 e_{it-1} + u_{it}$. One can show that a static regression of $\bar{Y}_{iK}$ on $\bar{X}_{iK}$ will produce a $\sqrt{N}K$ consistent estimate of the long-run multiplier $\theta = \frac{\beta_0 + \beta_1}{1 - \kappa(\beta_0 + \beta_1)}$ when K is large in spite of two biases: a misspecification bias from omitting $\Delta\bar{X}_{iK}$, and an endogeneity bias because $\text{cov}(\bar{X}_{iK}, \bar{e}_{iK}) \neq 0$. It is worthy emphasizing the mechanism:- $\text{var}(\bar{X}_{iK})$ has a stronger signal than the non-zero covariances induced by the biases. Even if we estimate a ADL model with a lagged dependent variable, Nickell bias will vanish as K increases, as we will show in simulations.

5.2 Deterministic Trends

If x_{it} is a unit root process with drift g_i, ie $\Delta x_{it} = g_i + u_{it}$. Then for $t \in [T_0+1, T_1]$,

$$x_{it} = x_{i,T_0} + g_i(t - T_0) + \sum_{s=T_0+1}^{t} u_{is}$$

is driven by both a deterministic and a stochastic trend. Averaging over K periods give

$$\bar{X}_{iK} = x_{i,T_0} + g_i \frac{K+1}{2} + \sum_{s=T_0+1}^{T_1} u_{is}$$

since $\frac{1}{K}\sum_{t=T_0+1}^{T_1}(t - T_0) = \frac{K+1}{2}$. The cross-section variance

$$\text{var}_i(\bar{X}_{iK}) \quad = \quad \text{var}_i(x_{i,T_0}) + \left(\frac{K+1}{2}\right)^2 \text{var}_i(g_i) + a_K \mathbb{E}_i[\sigma_i^2] \approx \frac{K^2}{4}\text{var}_i(g_i) + O(K)$$

for large K. The fanning out effect is thus larger than when the drift $g_i = 0$, but only if there is heterogeneity in g_i. The asymptotic variance is $Q_{XX}^{-1} V_K Q_{XX}^{-1}$. We already have $Q_{XX} = \text{var}_i(\bar{X}_{iK}) = O(K^2)$. Now $\bar{X}_{iK} - \mu_X = \frac{K}{2}(g_i - \mathbb{E}_i(g)) + \sum_{s=T_0+1}^{t} u_{is} = O(K)$, and $\bar{e}_{iK} = O(K^{-1/2})$. Thus, $\text{var}_i((\bar{X}_{iK} - \mu_)\bar{e}_{iK}) = O(K)$. The asymptotic variance is thus $O(K^{-4})O(K) = O(K^{-3})$. The estimator in the static regression is thus $\sqrt{N}K^{3/2}$, faster than the $\sqrt{N}K$ rate in the absence of the drift.

6 Long Differencing

The class of functions satisfying Theorem 1 is large, but there are also time compression functions that do not fit into that class. Simple long differencing and long differencing of averaged data (LD) are two examples. LD is based on a difference of the local averaging of $M = 2m + 1$ observations centered at T_0 and T_1, with $K = T_1 - T_0$. Unlike K period averaging, it requires an additional parameter, m. The popularity of LD could be due to its diff-in-diff flavor, the properties of transformed data are not well understood. Burke and Emerick (2016) simulate x_{it} as having a deterministic trend and show that if $K = T_1 - T_0$ is sufficiently large, the LD estimates from a cross-section regression are more precise than the ones obtained from a $T \times N$ panel of raw data.[6] We now analyze the LD assuming that x_{it} has a stochastic trend which seems to be a better characterization of the data.

[6] Burke and Emerick (2016) simulated $x_{it} = \theta t + w_{it}$ and $y_{it} = \alpha_{is} + \beta_{\bar{X}}\bar{X}_i + \beta_w w_{it} + \varepsilon_{it}$. Their regression also has a quadratic term that is not important for the arguments to follow. Arguably, it is the mean of $X_{is,t}^2$ that should be computed, not the square of the mean.

The LD transformation is actually the same filter used in Kutznets (1958) in report evidence of a 20-year cycle. However,. Howrey (1968) the cycle could be an artifact of long-differencing time-averaged data, as a cycle with the a 20 year periodicity could be found even if the raw data were a white noise.[7] For stationary data, it is known that averaging attenuates the high frequency variations and differencing attenuates the low frequency variations. For regressions, Engle and Liu (1972) show that a dynamic regression using averaged data will yield biased estimates because of correlation between the error term and the regressors. What makes the LD work is that transformation is applied only at $t = T_0$ and T_1 with the effect of collapsing the time variations into $\widetilde{X}_{iK} = \bar{X}_{iM}(T_1) - \bar{X}_{iM}(T_0)$, and then using the cross-section variation in estimation. This is unlike in time series regression based on dynamic correlations that are distorted by the transformation.

We will now argue that Theorem 1 does not apply to LD because the conditions on $w(t)$ are not satisfied. An example makes this clear. Suppose that $T_0 = 4, T_1 = 10$, $m = 1$ and thus $M = 3$. The observation and innovation weights are as follows:

		3	4	5	6	7	8	9	10	11	12	
$\widetilde{w}(t)$	..	$-\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{1}{3}$	0	0	0	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	0	..
$\widetilde{\phi}_s$	..	0	$\frac{1}{3}$	$\frac{2}{3}$	1	1	1	1	$\frac{2}{3}$	$\frac{1}{3}$	0	..

Several features are of note: (i) $\widetilde{w}(t) < 0$ for some t, (ii) $\sum_t w(t) = 0$. Hence both conditions required for Theorem 1 to hold are violated. Furthermore, (iii) the initial condition x_{i,T_0} is not used; (iv) $\widetilde{\phi}_s$ jumps from 0 to $1/M$ at $T_0 - m + 1$, and from $1/M$ to 0 at $T_1 + m + 1$. For I(1) variables, LD puts a weight of 1 on the $K - M + 1$ innovations that are in the middle, while the observations at the two end points have smaller weights. The 'tent' pattern of $\widetilde{\phi}_s$ generalizes[8] to yield

$$\text{var}(\widetilde{X}_{iM}) = \omega_i^2 \left((K - M + 1) + 2 \sum_{j=1}^{2m} (j/M)^2 \right) = \omega_i^2 \left(K - \frac{M^2 - 1)}{3M} \right).$$

If we let $K \to \infty$ keeping M and T_0 in LD fixed, then $\text{var}(\widetilde{X}_{iK}) = \omega_i^2 K$. This is three times larger than $\text{var}(\bar{X}_{iK}) = \omega_i^2 K/3$ from simple averaging, a consequence of the fact that when $K \to \infty$ with M fixed, $K - M + 1$ innovations will receive a full weight of 1. In contrast, simple averaging gives a flat weight to the observations and triangular weights to the innovations.

It is useful to compare LD with K averaging when both use the maximum of the sample size, being T. With K averaging, we set $T_0 = 1$ and $T_1 = T$ so that with $K = T$, we obtain

[7] Amemiya and Wu (1972) shows that if x_t is a stationary AR(p), time averaging overlapping data $\bar{X}_t$ is ARMA(p,q), where q is at most p.

[8] We have used $2\sum_{j=1}^{2m}(j/M)^2 = \frac{(M-1)(2M-1)}{3M}$ and $M = 2m + 1$ to simplify.

$\text{var}(\bar{X}_{iK}) = \omega_i^2 c_T$. With LD, the largest span is $T-2m$, obtained by setting $T_0 = m$ and $T_1 = T-m$ to yield $\text{var}(\widetilde{X}_{iK}) = \omega_i^2(T - M + 1 - \frac{M^2-1}{3M}$. The LD variance is smaller than K averaging if and only if $M < 3T/4$, or $m < T/3$. Once the window width of $M = 2m+1$ is larger than $3T/4$, there will not be enough observations that receive unit weighting to realize the variance advantage over simple averaging. The choice of m is thus important. In this regard, we note that Dell et al. (2012) report 'medium-term' effects using two 15-year averages positioned 15 years apart (i.e., $m = 7$ and $K = 15$), which implies $K - M$ is small. In contrast, Burke and Emerick (2016) report 'longer-term effects' using $m = 2$ and $K = 20$, and thus $K - M$ is much larger.

Though the signal in $\text{var}_i(\widetilde{X}_{iK})$ for LD is larger, $\widetilde{e}_{iK} = \bar{e}_{iM}(T_1) - \bar{e}_{iM}(T_0)$, $\text{var}_i(\widetilde{e}_{iK}) = 2\tau_i^2/M$, compared to $\text{var}_i(\bar{e}_{iK}) = \tau_i^2/K$ for K averaging. Though LD has more noise, the LD does seem to have efficiency advantage in a regression of $\widetilde{Y}_{iK}$ on $\widetilde{X}_{iK}$ with a suitable choice of M. If x_{it} is I(1), a static LD regression will give $\sqrt{N}K$ consistent estimates of β if the DGP is static , and $\sqrt{N}K$ consistent estimates of the long-run multiplier if the true model is the ADL(1,1) model. However, if estimate the ADL(1,1) modelc, Nickell bias still precludes consistent estimation of α for fix K, as with K averaging.

While the LD seems appealing when x is I(1), it has a major drawback when x is I(0). Consider the example above, but now $x_{it} = \rho x_{it-1} + u_{it}$ with $\rho < 1$ and $\widetilde{X}_{iM}(T_j) = \frac{1}{3}(x_{i,T_j-1} + x_{i,T_j} + x_{i,T_j+1})$. The weight on innovation u_{is} in $\bar{X}_{iM}(T_j)$ for $s \leq T_j - 1$ is:

$$\frac{1}{3}\left(\rho^{T_j-1-s} + \rho^{T_j-s} + \rho^{T_j+1-s}\right) = \frac{\rho^{T_j-1-s}(1+\rho+\rho^2)}{3}.$$

Denoting $\kappa = (1+\rho+\rho^2)/3$, the weights on u_{is} in $\widetilde{X}_{iK} = \widetilde{X}_{iM}(T_1) - \bar{X}_{iM}(T_0)$ are:

s	$\cdots$	3	4	5	6	7	8	9	10	11	$\cdots$
$w_0(s)$	$\cdots$	ϕ	$\frac{1+\rho}{3}$	$\frac{1}{3}$	0	0	0	0	0	0	$\cdots$
$w_1(s)$	$\cdots$	$\phi\rho^6$	$\phi\rho^5$	$\phi\rho^4$	$\phi\rho^3$	$\phi\rho^2$	$\phi\rho$	ϕ	$\frac{1+\rho}{3}$	$\frac{1}{3}$	$\cdots$
$w(s)$	$\cdots$	$\phi(\rho^6-1)$	$\phi\rho^5 - \frac{1+\rho}{3}$	$\phi\rho^4 - \frac{1}{3}$	$\phi\rho^3$	$\phi\rho^2$	$\phi\rho$	ϕ	$\frac{1+\rho}{3}$	$\frac{1}{3}$	$\cdots$
$\psi_s(\rho)$	$\cdots$	-0.574	-0.482	-0.297	0.073	0.146	0.292	0.583	0.500	0.333	$\cdots$

In the above, $\psi_s(\rho) = \sum_{t \geq s} w(t)\rho^{t-s}$ $w(s) = w_1 - w_0$. For $\rho = 1$, this reduces to a weight of 1 for $s = 6, 7, 8, 9$ obtained earlier. For $\rho < 1$, innovations d periods from the T_1 window receive weight ρ_i^d in $\bar{X}_{iM}(T_1)$, and the weight becomes negligible when ρ_i^d is small. In the end, $\text{var}(\bar{X}_{iM}(T_j)) \approx \omega_i^2/M$ as predicted by the theory for covariance stationary processes, but the rate does not change with K. Accordingly, the Q_{XX} is $O(M)$ for any K. The variance of $\widetilde{X}_{iK}$ is almost entirely driven by

innovations within $O(1/(1-\rho_i))$ periods of each window, leaving a lot of information unused. The last row shows $\psi_s(\rho)$ evaluated at $\rho = 0.5$. When $\rho_i = 0$ for example, $\text{var}(\widetilde{X}_{iK}) = 2\sigma_i^2/M$. In a sense, the effective sample size of an LD regression is M instead of K when x is stationary. As such, it does not enjoy the 'robustness' of simple averaging to whether x is I(1) or I(0). For example, the omitted variable $\widetilde{\eta}_{iK}$ is now correlated with $\widetilde{X}_{iK}$. The fix K bias from estimating the long run multiplier using $\bar{X}_{iK}$ is now $O(M^{-1})$ and does not vanish with K. Because time compression by LD cannot be analyzed within the framework of Lemma 1, we cannot establish the smooth transition property enjoyed by K averaging. Nonetheless, interesting features are revealed in simulations.

7 Simulations

This section evaluates estimates from cross-section, and panel regressions using time averaged data. We first consider models that specify x_{it} as the sum of a stationary and a non-stationary component. We then specify a bivariate model where x_{it} may not be stationary or exogenous.

We suppose that we have data $\{y_{ist}, x_{ist}\}$ for $s = 1, \ldots, S$ locations, $i = 1, \ldots N$ units, and $t = 1, \ldots, T$ time periods. We consider the following regressions (which can be static or dynamic):

1. T: time series regressions with T observations at give $(i, s) = (i_*, s_*)$.
2. S or N: : cross section regressions each with N or S observations of averaged data.
3. SN: panel effect regression using a $S \times N$ data matrices at given $t = t^*$.
4. LD: long-difference regression using the difference of averaged data centered at T_0 and T_1

The first set of simulations are conducted as follows. For each $i = 1, \ldots, N$, $s = 1, \ldots, S$ and $t = 1, \ldots, T$, data are generated as

$$\begin{aligned} y_{is,t} &= \beta_\mu \mu_{is,t} + \beta_w w_{is,t} + e_{is,t} \\ x_{is,t} &= \mu_{is,t} + w_{is,t}, \\ w_{is,t} &= \rho w_{is,t-1} + \varepsilon_{is,t}. \end{aligned}$$

The non-stationary x_{it} is modeled as the sum of a stationary cocmponent w_{it}, and a non-stationary component $\mu_{is,t}$. We let q_i be signal of the non-stationary to the stationary component. Let $u_{it} \sim (0, \sigma_u^2)$ and $w_{it} \sim (0, \sigma_w^2)$ be mutually uncorrelated but possibly serially correlated. We consider two models that seem relevant for the temperature series.

1. local level model where $\mu_{is,t} = \mu_{is,t-1} + u_{is,t}$ with $q_i = \frac{\sigma_u^2}{\sigma_w^2}$:

2 factor model: $\mu_{is,t} = \lambda_{is}\mu_t + u_{is,t}$ where $\mu_t = \mu_{t-1} + u_t$, $\lambda_{is} \sim (0, \sigma_\lambda^2)$. with $q_i = \frac{\sigma_\lambda^2 \sigma_u^2}{\sigma_w^2}$.

The local-level model provides a permanent-transitory decomposition of the data and one can think of $\mu_{is,t}$ as a time varying intercept. The factor model provides a common-idiosyncratic representation of the data; non-stationary comes from the common trend μ_t. Both models imply a reduced form $\Delta x_{it} = \epsilon_{it} + \vartheta_i \epsilon_{it-1}$ where $\vartheta_i = \Big[-(q_i + 2) \pm \sqrt{q_i^2 + 4q_i} \Big]/2$. Of note is that $\vartheta_i \to 0$ as $q_i \to \infty$ and $\vartheta_i \to -1$ if $q_i \to 0$. As noted above, the cross-section variance fans out at rate K, but has a proportional factor that depends on $\mathbb{E}_i[(1 + \vartheta_i)^2 \sigma_i^2]$.

In the simulations, we let $e_{is,t} \sim N(0, 1)$. $\varepsilon_{is,t} \sim N(0, 1)$, $\rho = 0$ or 0.5, $\beta_\mu = -1$ and $\beta_w = -2.5$. The nonstationary component $\mu_{is,t}$ is either ξ_{ist} in the local level model with innovation variance σ_u^2, or the common component, where the random walk ξ_t has unit innovation variance and loadings $\lambda_i \sim (0, \sigma_\lambda^2)$. As discussed above, the relative importance of the two components is driven by the signal-to-noise ratio. Thus, we consider different values of σ_u^2 and σ_λ^2 and the implied moving-average parameter ϑ.

Table 2 presents estimates and corresponding standard errors, obtained from 1,000 replications, from several cross-section regressions for different values of σ_u (or σ_λ), ρ and the implied ϑ. The true values of the regression coefficients are $(\beta_\mu, \beta_w) = (-1, -2.5)$ and the sample size is $(T, N, S) = (50, 50, 50)$. The estimates from the infeasible regression on $\mu_{is,t}$ and $w_{is,t}$, which are not observed by the econometrician, are labeled ORACLE. In practice, the econometrician observes only $x_{is,t}$ and not its individual components. The feasible regression of y on x yields the cointegrating vector. As $\text{cov}(x, y) = \beta_\mu \text{var}(\mu) + \beta_w \text{var}(w)$, we have

$$\beta_X = \beta_\mu \frac{\text{var}(\mu)}{\text{var}(x)} + \beta_w \frac{\text{var}(w)}{\text{var}(x)}.$$

'S' denotes a cross-section regression of S observations sampled at $T_1 = 20$, $T = 50$ and averaged from 1 to T. 'S-CA' denotes a cross-section regression of centered averaged $k = 9$ observations around $T_0 = 10$ and $T_2 = 40$ while 'S-PA' stands for cross-section regressions with partial averaging between T_0 and T_1, and between T_1 and T_2. Finally, '$LD_K(T_0, T_2, m)$' is a long-differenced regression between T_2 and T_0, with averaging of m observations around these two time periods.

Even though the non-stationary variations should dominate when T is large, in finite samples the least squares estimate $\hat{\beta}_X$ will be a weighted sum of β_μ and $\beta_w$with weights that depend on the signal-noise-ratio, with an indicator being ϑ. Regardless of data used, we see that $\hat{\beta}_\mu$ is close

to β_μ when ϑ is away from -1, but is contaminated by β_w as ϑ moves closer to -1. Even though all methods give somewhat similar estimates, the standard errors are largest when the raw data are used and are smallest with partial averaging, especially if the averaging is performed over the whole time dimension $1:T$. Overall, averaging and using information later in the sample helps while long differencing adds little benefit.

The finite-sample size and power properties of a t-test based on these methods are presented in Table 3. The values of ϑ are based on two values of ρ, the persistence of the stationary component. When $\vartheta = 0$, x is a pure random walk. The fanning out effect is smaller when $\vartheta = -0.5$. These results suggest that inference, based on the limiting distribution of the time compressed estimators with $w(t)$ satisfying Theorem 1, are quite well approximated by the normal distribution, and the tests appears to be quite reliable. Though tests based on LD data also have good size, they have limited power.

Table 4 reports estimates and standard errors from panel regressions (SN panel) with fixed effects. The methods are denoted similarly as in Table 2 with 'S' replaced by 'SN'. Again, the SN regression with averaged data over the whole time period $(1:T)$ appears to estimate most accurately the coefficient β_μ on the nonstationary component with the estimates being contaminated with β_w as the signal from the nonstationary component (σ_u and σ_λ) decreases.

In the final experiment, we relax strict exogeneity and consider the bivariate system:

$$\underbrace{\begin{pmatrix} 1 & 0 \\ -\beta_0 & 1 \end{pmatrix}}_{B_0}\underbrace{\begin{pmatrix} x_t \\ y_t \end{pmatrix}}_{z_t} = \underbrace{\begin{pmatrix} \rho & \gamma \\ \beta_1 & \alpha \end{pmatrix}}_{B_1}\underbrace{\begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix}}_{z_{t-1}} + \underbrace{\begin{pmatrix} e_{xt} \\ e_{yt} \end{pmatrix}}_{e_t}, \quad \begin{pmatrix} e_{xt} \\ e_{yt} \end{pmatrix} \sim WN\left(0, \begin{pmatrix} \sigma_y^2 & 0 \\ 0 & \sigma_x^2 \end{pmatrix}\right), \tag{2}$$

The system is stable if the maximum eigenvalue of $A = B_0^{-1}B_1$ is less then one. The matrix of dynamic mulipliers at lag h is $C_h = A^h B_0^{-1}$, and the matrix of long run multipliers is $C(1) = (I_2 - A)^{-1}B_0^{-1}$. The system long-run multiplier of x on y, denoted θ^*, is then the $(2,1)$ entry of $C(1)$. Specifically,

$$\theta^* = \frac{\beta_0 + \beta_1}{(1-\alpha)(1-\rho) - \kappa(\beta_0 + \beta_1)}.$$

Finally, Table 5 presents the results from a dynamic panel estimation of the bivariate dynamic model along with the implied estimates of $\theta^\dagger$ and θ^*. 'SN-ADL(1,1)' reports the estimates from the first (ADL(1,1)) equation and 'SN-System' also reports the estimates from the second equation. Overall, the model parameters and long-run effects are very precisely estimated and are largely robust to the value of ρ. It is also notable that there is practically no downward bias in $\hat{\rho}$ which, in turn results in very accurate estimates of θ^*.

8 Conclusions

Temperature data tend not to be stationary, and estimating the effect of temperature on growth at any horizon must confront this fact. This paper considers regressions using time-compressed data in this context. The main result is that if the regressor is nonstationary, time compression (removing the T dimension of the data), such as by time averaging, can yield (super-)consistent and asymptotically normal estimates which obviates the need for unit-root asymptotics. The key mechanism is that the paths of the I(1) variables across units 'fan out' with time. Time averaging amplifies the signal in the I(1) regressor and dampens the stationary regression noise; it also makes endogeneity and misspecification bias of second order. We show that a class of time compression functions allows smooth transition of the asymptotic distribution from I(1) to I(0), with the implication that standard normal inference can be used irrespective of the degree of persistence in the regressors. We use simulations to verify the finite-sample properties of estimates in static and dynamic regressions using time compressed data.

Appendix

Suppose that the scalar series x_t is stationary. Then, $\sqrt{T}\bar{X} \xrightarrow{d} N(0, \omega_x^2)$ where $\omega_x^2 = 2\pi \sum_{j=-\infty}^{\infty} \gamma(j))$ is the long-run variance of x. If $\Delta x_t = v_t$, $v_t \sim (0, \sigma^2)$ and is serially correlated with long run variance ω_v^2, then $\frac{\bar{X}}{\sqrt{T}} = T^{-3/2} \sum_{t=1}^{T} x_t \Rightarrow \omega_v^2 \int_0^1 W(r)dr = A$. Since $\mathbb{E}[\int_0^1 W(r)dr]^2 = 1/3$, $\text{var}(T^{-1/2}\bar{X}) = \omega_v^2/3$ when x_t is I(1).

In what follows, we will use $\mathbb{E}_i[\,\cdot\,]$ and $\text{Var}_i(\,\cdot\,)$ to denote expectation and variance over the cross-sectional distribution of units.

Proof of Lemma 1

Consider Since $x_{it} = x_{i,t-1} + u_t$, $x_{it} = x_{i,T_0} + \sum_{s=T_0+1}^{t} u_{is}$. averaging $K = T_1 - T_0$ observations. $\bar{X}_{i,K} = x_{i,T_0} + \frac{1}{K} \sum_{t=T_0+1}^{T_1} \sum_{s=T_0+1}^{t} u_{is}$. Since u_{is} in the double sum for $t = s$ to $s = T_1$ appears $T_1 - s + 1$ times, and $T_1 - s + 1 = K - (s - T_0) + 1$, we can let $j = T_1 - s + 1$ to obtain

$$\begin{aligned} \bar{X}_{iK} &= x_{i,T_0} + \sum_{s=T_0+1}^{T_1} \frac{T_1 - s + 1}{K} u_{is} = x_{i,T_0} + \sum_{j=1}^{K} \frac{(K - j + 1)}{K} u_{i,T_0+j} \\ &= x_{i,T_0} + \sum_{j=1}^{K} \phi_j u_{i,T_0+j}, \qquad \text{where} \quad \phi_j = \frac{K - j + 1}{K}. \end{aligned}$$

Note that $\mu_X = \mathbb{E}_i[\bar{X}_{iK}] = \mathbb{E}_i[x_{i,T_0}]$, because u_{it} have mean zero. We thus have $\text{var}(\bar{X}_{iK}) = T_0\omega_i^2 + a_K\omega_i^2$. Therefore, $\text{var}_i(\bar{X}_{iK}) = \text{var}_i(x_{i,T_0}) + a_K\mathbb{E}_i[\omega_i^2]$, where $\text{var}_i(x_{i,T_0}) = \mathbb{E}_i[(x_{i,T_0} - \mu_X)^2]$ is the cross-section variance of initial conditions.

Proof of Proposition 1

The OLS estimator satisfies:

$$\hat{\beta} - \beta = \frac{\frac{1}{N}\sum_i (\bar{X}_{iK} - \bar{\bar{X}})\, \bar{e}_{iK}}{\frac{1}{N}\sum_i (\bar{X}_{iK} - \bar{\bar{X}})^2}.$$

Part (i): K fixed By LLN, the denominator converges to the fixed constant:

$$Q_{XX} \equiv \text{var}_i(\bar{X}_{iK}) = a_K\, \mathbb{E}_i[\sigma_i^2] + \mathbb{E}_i[var(x_{i,T_0})].$$

Since $E[u_{is}e_{it}] = 0$ for all t, s by assumption, a CLT applies to the numerator $\frac{1}{\sqrt{N}}\sum_i(\bar{X}_{iK} - \bar{\bar{X}})\bar{e}_{iK}$ and gives a mean zero process with variance:

$$V_K = \mathbb{E}_i\left[(\bar{X}_{iK} - \mu_X)^2\,\bar{e}_{iK}^2\right] = \mathbb{E}_i\left[(\bar{X}_{iK} - \mu_X)^2\,\frac{\tau_i^2}{K}\right] = \frac{a_K\,\mathbb{E}_i[\omega_i^2\tau_i^2] + \mathbb{E}_i[(x_{i,T_0} - \mu_X)^2\tau_i^2]}{K}$$

since $u_{it} \perp e_{is}$ by assumption. Combining the results for the numerator and denominator gives the variance stated in the Proposition.

Part (ii): $K \to \infty$ With large K, $a_K = (K+1)(2K+1)/(6K) \approx K/3$ and term relating to the initial condition becomes negligible. Now $Q_{XX}^{-2}V_K = O(K^{-2})$. Multiplying the estimator by K $\sqrt{N}K(\hat{\beta} - \beta) \xrightarrow{d} N(0, \mathcal{Q}_{XX}^{-1}\mathcal{V}\mathcal{Q}_{XX}^{-1})$. For this model, we obtain a non-degenerate limit, $\mathcal{V} = \mathbb{E}_i[\omega_i^2\tau_i^2]/3$ and $\mathcal{Q}_{XX} = \mathbb{E}_i[\omega_i^2]/3$, giving an asymptotic variance of $3\mathbb{E}_i[\omega_i^2\tau_i^2]/(\mathbb{E}_i[\omega_i^2])^2$.

Proof of Proposition 2:

Now the DGP is the ADL(1,1) model. We use the Bewley transformation to obtain

$$y_{it} = \theta x_{it} - \alpha^*\Delta y_{it} - \beta^*\Delta x_{it} + + e_{it}^*,$$

where $\theta = \frac{(\beta_0+\beta_1)}{1-\alpha}$, $\alpha^* = \frac{\alpha}{1-\alpha}$, $\beta_1^* = \frac{\beta_1}{1-\alpha}$, and $e_{it}^* = \frac{e_{it}}{1-\alpha}$. Averaging over K gives

$$\bar{Y}_{iK} = \theta - \underbrace{(\alpha^*\Delta y_{iK} + \beta_1^*\Delta x_{iK})}_{\eta_{iK}} + \bar{e}_{iK}^*,$$

where $y_{iK} = \Delta y_{iK} = \frac{(y_{i,T_1} - y_{i,T_0})}{K} = O_p(K^{-1/2})$ and $x_{iK} = \frac{(x_{i,T_1} - x_{i,T_0})}{K} = O_p(K^{-1/2})$ only depend on the endpoint observations.. The static regression is $\bar{Y}_{iK} = c + \beta\bar{X}_{iK} + \text{error}$, where error$= -\eta_i + \bar{e}_{iK}$. Since x depends on u and $\mathbb{E}[u_{is}e_{it}]$ for all s and for every i, $\text{cov}(\bar{X}_{iK}, \bar{e}_{iK}) = 0$. But $\eta_{iK} = O_p(K^{-1/2})$, which is the same order as $\text{var}_i(\bar{e}_{iK})$. By Cauchy Schwarz inequality,

$$|\text{cov}_i(\bar{X}_{iK}, \eta_{iK})| \leq \sqrt{\text{var}_i(\bar{X}_{iK})}\sqrt{\text{var}_i(\eta_{iK})} = O(K^{1/2})O(K^{-1/2}) = O(1).$$

The effects of the omitted variables do not vanish with K. However, $\text{var}_i(\bar{X}_{iK}) = O(K)$. Thus, for fixed K,

$$\text{plim}\hat{\beta} = \theta - \frac{\text{cov}_i(\bar{X}_{iK}, \eta_{iK})}{\text{var}_i(\bar{X}_{iK})}$$

and

$$\sqrt{N}\left(\hat{\beta} - \theta + \frac{\text{cov}_i(\bar{X}_{iK}, \eta_{iK})}{\text{var}_i(\bar{X}_{iK})}\right) \xrightarrow{d} N(0, Q_{XX}^{-1}W_K Q_{XX}^{-1}),$$

where $W_K = \text{var}_i((\bar{X}_{iK} - \mu_X)(\bar{e}_{iK} - \eta_{iK})$. Though $\bar{e}_{iK}$ does not contribute to bias, it contributes to variance. For large K,

$$\frac{\text{cov}_i(\bar{X}_{iK}, \eta_{iK})}{\text{var}_i(\bar{X}_{iK})} = \frac{O(1)}{O(K)} = O(K^{-1}) \to 0$$

and with $\mathcal{W} = \lim_{K\to\infty} W_K$ and $\mathcal{Q}_{XX} = \lim_{K\to\infty} KQ_{XX}$, we have

$$\sqrt{N}K(\hat{\beta} - \theta) \xrightarrow{d} N(0, \mathcal{Q}_{XX}^{-1}\mathcal{W}\mathcal{Q}_{XX}^{-1}).$$

Proof of Proposition 3

We now let $x_{it} = \rho_i x_{it-1} + u_{it}$, where $u_{it} \sim (0, \sigma_i^2)$ and $\omega_i^2 = \frac{\sigma_i^2}{(1-\rho_i^2)}$ is the long-run variance of x_{it}. It follows from the theory of covariance stationary processes that $\text{var}(\bar{X}_{iK}) = \frac{\omega_i^2}{K}$, and $\bar{X}_{iK} = O_p(K^{-1/2})$.

For part (i), when the static model is correctly specified, it follows from $\text{cov}_i(\bar{X}_{iK}, \bar{e}_{iK}) = 0$ that $\sqrt{N}(\hat{\beta} - \beta) \xrightarrow{d} N(0, Q_{XX}^{-1}V_K Q_{XX}^{-1})$, where $V_K = \text{var}_i((\bar{X}_{iK} - \mu_X)\bar{e}_{iK})$ for all K.

For part (ii), the omitted variables are collected in

$$\eta_{iK} = \frac{\alpha\Delta y_{iK} + \beta_1 \Delta x_{iK}}{1 - \alpha} = O_p(K^{-1})$$

since $\Delta x_{iK} = \frac{1}{K}(x_{i,T_1} - x_{i,T_0}) = O_p(K^{-1})$, and similarly, $\Delta y_{iK} = O_p(K^{-1})$. Though the bias is shrinking faster than in the I(1) case, $\bar{X}_{iK} = O_p(K^{-1/2})$, so the omitted variable bias is $OK(K^{-1/2})$, which is larger than in the I(1) case.

Proof of Proposition 4

We consider the reparameterized model

$$\bar{Y}_{iK} = \alpha \bar{Y}_{iK,-1} + \underbrace{(\beta_0 + \beta_1)}_{\delta_0} \bar{X}_{iK} \underbrace{-\beta_1}_{\delta_1} \Delta\bar{X}_{iK} + \bar{e}_{iK}$$

Since $Y_{iK} = O(K^{1/2})$ when x and thus y is non-stationary, Nickell bias in the I(1) case is

$$NB = \frac{\text{cov}_i(\bar{Y}_{iK,-1}, \bar{e}_{iK})}{\text{var}_i(\bar{Y}_{iK,-1})} = \frac{O(K^{-1})}{O(K)} = O(K^{-2}) \to 0.$$

However, in the I(0) case, x is stationary and thus $\text{var}_i(\bar{Y}_{iK,-1}) = O(K^{-1})$. Furthermore, analogous to dynamic panel regressions,

$$\text{cov}(\bar{Y}_{iK,-1}, \bar{e}_{iK}) = \frac{\tau_i^2}{K^2(1-\alpha)}\left[K - \frac{1-\alpha^K}{1-\alpha}\right]$$

which is $O(K^{-1})$ for large K. Thus, in the I(0) case, NB=O(1) and does not change with K.

Proof of Theorem 1

Since $x_{it} = x_{it-1} + u_{it}$, $x_{it} = x_{i,T_0} + \sum_{s=T_0+1}^{t} u_{is}$. The weighted average $\bar{X}_i = \sum_t w(t)x_{it}$ with $w_t > 0$ and $\sum_t w(t) = 1$. More generally,

$$\bar{X}_{iK} = \sum_{t=T_0+1}^{T_1} w(t)\left(x_{i,T_0} + \sum_{s=T_0+1}^{t} u_{is}\right) = x_{i,T_0} + \sum_{t=T_0}^{T_1} w(t) \sum_{s=T_0+1}^{t} u_{is}.$$

Reversing the order of summation to sum over s first, then over all $t \geq s$, we have $\bar{X}_{iK} = x_{i,T_0} + \sum_{s=T_0+1}^{T_1} u_{is} \sum_{t=s}^{T_1} w(t)$. Defining $\phi_s \equiv \sum_{t=s}^{T_1} w(t)$ yields:

$$\widetilde{X}_i = x_{i,T_0} + \sum_{s=T_0+1}^{T_1} \phi_s \, u_{is}, \qquad \phi_s \equiv \sum_{t=s}^{T_1} w(t), \tag{3}$$

where ϕ_s is the tail sum of w at s, and the sequence $\{\phi_s\}$ is the survival function of the weight distribution w. Since $\phi_s \in [0,1]$ for any non-negative w such that $\sum_{t=T_0+1}^{T_1} w(t) = 1$, we have $\phi_s^2 \leq \phi_s$ for each s. Consider now

$$\sum_{s=T0+1}^{T_1} \phi_s = \sum_{s=T_0+1}^{T_1} \sum_{t=s}^{T_1} w(t) = \sum_{t=T_0+1}^{T_1} w(t) \sum_{s=T_0+1}^{t} 1 = \sum_{t=T_0+1}^{T_1} w(t)(t-T_0) = K\mathbb{E}_w\left[\frac{t-T_0}{K}\right].$$

For any non-degenerate w, $\mathbb{E}_w[(t - T_0/K] = O(1)$. Thus $\sum_s \phi_s = O(K)$ and $\sum_{s=T_0+1}^{T_1} \phi_s^2 = O(K)$.

In the stationary case, we have, by definition,

$$\text{var}(\widetilde{X}_{iK}) \quad = \quad \sum_{s=T_0+1}^{T_1} \sum_{t=T_0+1}^{T_1} w(t)w(s)\text{cov}(x_{it}, x_{is}).$$

Consider $x_{it} = \rho x_{i,t-1} + u_{it} = \sum_{s=0}^{\infty} \rho_i^s u_{t-s}$ where $u_{it} \sim (0, \sigma_i^2)$, we have $\bar{X}_{iK} = \sum_s \psi_s(\rho_i)u_{is}$ with

$\psi_s(\rho_i) = \sum_{t=s}^{T_1} w(t)\rho_i^{t-s}$ and $\text{cov}(x_{it}, x_{is}) = \frac{\sigma_i^2}{1-\rho_i^2}\rho_i^{|t-s|}$. Thus

$$\begin{aligned}
\text{var}(\widetilde{X}_{iK}) &= \frac{\sigma_i^2}{1-\rho_i^2} \sum_{h=-(K-1)}^{(K-1)} \sum_{t=-s=h} w(t)w(s)\rho_i^{|t-s|} \\
&= \frac{\sigma_i^2}{1-\rho_i^2} \sum_{h=(K-1)}^{K-1} A_h \rho_i^{|h|} = \frac{\sigma_i^2}{1-\rho_i^2} G(\rho_i) \\
&\equiv \sigma_i^2 \Psi_K(\rho)
\end{aligned}$$

where $A_h = \sum_{t-s=h} w(t)w(s)$, and $\Psi_K(\rho) = \frac{1}{1-\rho_i^2} G(\rho_i)$. But $A_h > 0$ and $\sum_h A_h = (\sum_t w(t))^2 = 1$, so $\{A_h\}$ forms a probability distribution over the lags. Thus, $G(\rho_i) = \mathbb{E}_A[\rho_i^{|h|}]$. Since $0 \leq \rho_i^{|h|} \leq 1$ for any $|\rho_i| \leq 1$, $0 \leq G(\rho_i) \leq 1$ for any $\rho_i \in [0,1]$ and any w. In the local to unity framework, $\rho_i^{|h|} = (1 - c_i/K)^{|h|} \approx 1 - \frac{c_i|h|}{K}$. Thus, $G(\rho_i) = \mathbb{E}_w[1 - \frac{|h|a_i}{K}] = 1 - \frac{c_i}{K}\mathbb{E}_w[|h|]$. For simple averaging, $\mathbb{E}_A[|h|] \approx K/3$ and thus $G(\rho_i) \approx 1 = O(1)$. The order of Ψ_K is fundamentally determined by ρ_i and not about the choice of $w(t)$, so long as it satisfies $w(t) \geq 0$ and $\sum_t w(t) = 1$.

For simple averaging, the result is immediate since $\text{var}(\bar{X}_{iK}) = \frac{1}{K}\frac{\sigma_i^2}{(1-\rho_i)^2}$. In the local-to-unity case when $\rho_i = 1 - c_i/K$, $\omega_i^2 = K^2\sigma^2/a_i^2$, implying $\Psi_K = O(K)$. Thus $\text{var}_i(\bar{X}_{iK}$ behaves as if $\rho_i = 1$, and $Q_{XX} = O(K)$ in the local-to-unity setting.

Relaxing Strict Exogeneity

$$\text{cor}(u_{it}, e_{is}) = \gamma_{i,t-s}, \qquad \text{or} \qquad \text{cov}(u_{it}, e_{is}) = \gamma_{i,t-s}\sigma_i\tau_i$$

Using $\bar{X}_{iK} = x_{i,T_0} + \sum_s \phi_s u_{is}$ and $\bar{e}_{iK} = \sum_t w(t)e_{it}$,

$$\begin{aligned}
\text{cov}(\bar{X}_{iK}, \bar{e}_{iK}) &= \text{cov}\left(x_{i,T_0} + \sum_s \phi_s u_{is},\ \sum_t w(t)e_{it}\right) \\
&= \sigma_i\tau_i \sum_s \sum_t \phi_s w(t)\gamma_{s-t} \\
&= \sigma_i\tau_i \sum_{h=-(K-1)}^{K-1} \gamma_{ih}B_h, \quad \text{where} \quad B_h = \sum_{s-t=h} \phi_s w(t)
\end{aligned}$$

where the last equality follows from grouping by lag $h = s - t$ from $-(K-1)$ to $(K-1)$, for $s, t \in [T_0 + 1, T_1]$. Note that B_h does not depend on i. For K averaging, $w(t) = 1/K$ and $\phi_s = \frac{(T_1 - s + 1)}{K}$. Thus

$$\sum_{s-t=h} \phi_s w(t) = \frac{1}{K} \sum_{\substack{s-t=h \\ T_0+1 \leq s,t \leq T_1}} \frac{T_1 - s + 1}{K} = \frac{1}{K} \sum_{j=h+1}^{K} \frac{(K - j + 1)}{K}.$$

When $j = h+1$, the term is $K-h$. When $j = h+2$, it is $K-h-1$, when $j = K$, it is 1. Changing index to let $m = K - j + 1$, we see that as j increases from $h+1$ to K, m decreases from $K-h$ to 1. Thus,

$$\frac{1}{K}\sum_{j=h+1}^{K}\frac{(K-j+1)}{K} = \sum_{m=1}^{K-h} m = \frac{1}{K^2}\frac{(K-h)(K-h+1)}{2} \to 1/2.$$

Since $|B_h| \leq 1/2$ and $\sum_h |\gamma_{ih}| < \infty$, as $K \to \infty$, $\sum_{h=-(K-1)}^{K-1} \gamma_{ih} B_h \to \frac{1}{2}\sum_{h-\infty}^{\infty} \gamma_{ih} = \frac{\Gamma_i}{2}$ where Γ is unweighted sum of cross-covariances, akin to the long-run variance.

Table 2: Cross-Section Regressions using Averaged Data

DGP: $y_{is,t} = \beta_\mu \mu_{is,t} + \beta_w w_{is,t} + e_{is,t}$, $(\beta_\mu, \beta_w) = (-1, -2.5)$,
Cross-section regression: $y_s = \beta_x x_s + error$,
$(T, S, N) = (50, 50, 50)$, $(T_0, T_1, T_2) = (10, 20, 40)$ and $k = 9$

Local-Level Model

σ_u	ρ	ϑ	Oracle		S			S-CA		S-PA		$LD_K(T_0, T_2, m)$		
			$\hat{\beta}^*_\mu$	$\hat{\beta}^*_w$	T_1	T	$1:T$	$T_0 \pm k$	$T_2 \pm k$	$T_0 : T_1$	$T_1 : T_2$	$m = 0$	$m = 4$	$m = 9$
1.00	0.00	-0.38	-1.000	-2.501	-1.074	-1.029	-1.002	-1.020	-1.005	-1.012	-1.003	-1.093	-1.013	-1.007
0.50	0.00	-0.61	-1.000	-2.501	-1.253	-1.111	-1.008	-1.075	-1.018	-1.044	-1.012	-1.313	-1.049	-1.027
0.20	0.00	-0.82	-1.001	-2.501	-1.835	-1.500	-1.045	-1.367	-1.103	-1.233	-1.068	-1.929	-1.258	-1.151
0.10	0.00	-0.90	-1.002	-2.500	-2.251	-2.005	-1.161	-1.843	-1.339	-1.633	-1.236	-2.294	-1.679	-1.462
1.00	0.50	-0.67	-1.001	-2.503	-1.096	-1.039	-1.007	-1.064	-1.015	-1.038	-1.011	-1.122	-1.042	-1.025
0.50	0.50	-0.79	-1.002	-2.502	-1.320	-1.145	-1.028	-1.226	-1.058	-1.140	-1.041	-1.391	-1.153	-1.093
0.20	0.50	-0.91	-1.005	-2.501	-1.942	-1.602	-1.155	-1.785	-1.299	-1.581	-1.221	-2.027	-1.616	-1.435
0.10	0.50	-0.95	-1.009	-2.501	-2.309	-2.096	-1.469	-2.219	-1.746	-2.073	-1.611	-2.340	-2.102	-1.928
			S.E.											
1.00	0.00	-0.38	0.021	0.066	0.066	0.041	0.010	0.034	0.016	0.025	0.013	0.075	0.027	0.020
0.50	0.00	-0.61	0.041	0.041	0.118	0.078	0.021	0.067	0.032	0.050	0.025	0.129	0.053	0.039
0.20	0.00	-0.82	0.103	0.030	0.187	0.151	0.051	0.139	0.078	0.113	0.062	0.189	0.116	0.090
0.10	0.00	-0.90	0.207	0.029	0.206	0.190	0.097	0.185	0.136	0.173	0.115	0.200	0.171	0.148
1.00	0.50	-0.67	0.035	0.092	0.070	0.043	0.016	0.052	0.024	0.038	0.020	0.079	0.039	0.030
0.50	0.50	-0.79	0.070	0.051	0.121	0.082	0.033	0.094	0.048	0.072	0.039	0.131	0.072	0.057
0.20	0.50	-0.91	0.175	0.030	0.177	0.149	0.077	0.137	0.102	0.128	0.087	0.177	0.123	0.111
0.10	0.50	-0.95	0.349	0.026	0.185	0.175	0.120	0.130	0.137	0.137	0.130	0.178	0.130	0.136

Factor Model

σ_λ	ρ	ϑ	Oracle		S			S-CA		S-PA		$LD_K(T_0, T_2, m)$		
			$\hat{\beta}^*_\mu$	$\hat{\beta}^*_w$	T_1	T	$1:T$	$T_0 \pm k$	$T_2 \pm k$	$T_0 : T_1$	$T_1 : T_2$	$m = 0$	$m = 4$	$m = 9$
1.00	0.00	-0.38	-1.000	-2.499	-1.383	-1.255	-1.060	-1.202	-1.095	-1.178	-1.093	-1.419	-1.159	-1.114
0.60	0.00	-0.55	-0.999	-2.501	-1.531	-1.363	-1.093	-1.303	-1.141	-1.262	-1.139	-1.587	-1.239	-1.173
0.40	0.00	-0.67	-0.999	-2.501	-1.687	-1.486	-1.134	-1.414	-1.198	-1.351	-1.189	-1.750	-1.335	-1.246
0.20	0.00	-0.82	-0.998	-2.500	-1.925	-1.697	-1.216	-1.610	-1.317	-1.512	-1.286	-1.990	-1.512	-1.389
0.00	0.00	-1.00	-0.003	-2.501	-2.496	-2.498	-2.496	-2.495	-2.499	-2.497	-2.495	-2.500	-2.499	-2.497
1.00	0.50	-0.38	-1.000	-2.502	-1.406	-1.272	-1.114	-1.341	-1.159	-1.295	-1.160	-1.453	-1.270	-1.206
0.60	0.50	-0.55	-1.000	-2.501	-1.593	-1.410	-1.182	-1.510	-1.253	-1.430	-1.242	-1.653	-1.417	-1.325
0.40	0.50	-0.67	-0.999	-2.501	-1.756	-1.543	-1.254	-1.663	-1.351	-1.558	-1.324	-1.822	-1.557	-1.444
0.20	0.50	-0.82	-0.999	-2.501	-1.996	-1.766	-1.393	-1.900	-1.537	-1.774	-1.477	-2.060	-1.786	-1.652
0.00	0.50	-1.00	-0.001	-2.501	-2.500	-2.501	-2.498	-2.497	-2.500	-2.499	-2.498	-2.500	-2.499	-2.499
			S.E.											
1.00	0.00	-0.38	0.028	0.058	0.447	0.391	0.203	0.350	0.268	0.343	0.270	0.444	0.315	0.269
0.60	0.00	-0.55	0.044	0.042	0.476	0.443	0.246	0.411	0.311	0.406	0.321	0.474	0.371	0.321
0.40	0.00	-0.67	0.063	0.033	0.480	0.472	0.291	0.454	0.354	0.452	0.366	0.469	0.419	0.369
0.20	0.00	-0.82	0.103	0.025	0.439	0.480	0.361	0.486	0.413	0.492	0.426	0.414	0.469	0.431
0.00	0.00	-1.00	0.070	0.020	0.146	0.152	0.143	0.142	0.140	0.144	0.141	0.150	0.142	0.146
1.00	0.50	-0.38	0.045	0.089	0.450	0.404	0.270	0.422	0.321	0.422	0.338	0.455	0.385	0.344
0.60	0.50	-0.55	0.073	0.057	0.478	0.455	0.334	0.468	0.380	0.474	0.397	0.475	0.442	0.407
0.40	0.50	-0.67	0.104	0.042	0.471	0.477	0.383	0.477	0.420	0.491	0.438	0.456	0.468	0.445
0.20	0.50	-0.82	0.171	0.029	0.414	0.469	0.438	0.439	0.457	0.474	0.476	0.383	0.460	0.468
0.00	0.50	-1.00	0.074	0.018	0.129	0.133	0.073	0.077	0.077	0.077	0.073	0.126	0.076	0.077

Table 3: Rejection Rates for t-test for $H_0 : \beta = -1$

Regression: $\bar{Y}_{iK} = \beta \bar{X}_{iK} + \bar{e}_{iK}$
$(T, S, N) = (50, 50, 50)$, $(T_0, T_1, T_2) = (10, 20, 40)$ and $k = 9$

β	ρ	ϑ	S			S-CA		S-PA		$LD_K(T_0, T_2, m)$		
			T_1	T	$1:T$	$T_0 \pm k$	$T_2 \pm k$	$T_0 : T_1$	$T_1 : T_2$	$m = 0$	$m = 4$	$m = 9$
-1.00	0.00	-0.00	0.071	0.075	0.072	0.059	0.068	0.089	0.079	0.080	0.086	0.090
-0.99	0.00	-0.00	0.067	0.083	0.354	0.095	0.186	0.121	0.228	0.073	0.119	0.162
-0.97	0.00	-0.00	0.101	0.163	0.937	0.232	0.651	0.359	0.819	0.114	0.320	0.500
-0.95	0.00	-0.00	0.231	0.462	1.000	0.631	0.989	0.824	1.000	0.193	0.782	0.947
-1.00	0.50	-0.50	0.071	0.074	0.073	0.058	0.068	0.090	0.079	0.078	0.086	0.089
-0.99	0.50	-0.50	0.067	0.083	0.353	0.096	0.185	0.121	0.229	0.073	0.118	0.163
-0.97	0.50	-0.50	0.101	0.163	0.937	0.232	0.651	0.356	0.819	0.115	0.319	0.500
-0.95	0.50	-0.50	0.230	0.465	1.000	0.631	0.989	0.824	1.000	0.193	0.781	0.947

x is generated by the local level model with $\sigma_u = 1$ and $\sigma_w = 0.01$. The two values of ϑ correspond to $\rho = (0, 0.5)$, where ρ is the persistence of the stationary component. If $\vartheta = 0$, x is a pure random walk.

Table 4: Panel Regressions Using Averaged Data: $(\beta_\mu, \beta_w) = (-1, -2.5)$

$(T, S, N) = (50, 50, 50)$, $(T_0, T_1, T_2) = (10, 20, 40)$ and $k = 9$

Local Level Model

σ_u	ρ	ϑ	Oracle		SN			SN-CA		SN-PA		$LD_K(T_0, T_2, m)$		
			$\hat{\beta}^*_\mu$	$\hat{\beta}^*_w$	T_1	T	$1:T$	$T_0 \pm k$	$T_2 \pm k$	$T_0 : T_1$	$T_1 : T_2$	$m = 0$	$m = 4$	$m = 9$
1.00	0.00	-0.38	-1.001	-2.503	-1.072	-1.029	-1.002	-1.019	-1.004	-1.011	-1.003	-1.094	-1.012	-1.007
0.50	0.00	-0.61	-1.003	-2.501	-1.251	-1.111	-1.007	-1.074	-1.017	-1.042	-1.011	-1.316	-1.048	-1.027
0.20	0.00	-0.82	-1.007	-2.500	-1.834	-1.500	-1.042	-1.368	-1.101	-1.230	-1.066	-1.937	-1.256	-1.151
0.10	0.00	-0.90	-1.013	-2.500	-2.251	-1.999	-1.156	-1.848	-1.336	-1.629	-1.233	-2.304	-1.677	-1.463
1.00	0.50	-0.67	-1.002	-2.505	-1.094	-1.039	-1.007	-1.064	-1.015	-1.037	-1.010	-1.122	-1.041	-1.024
0.50	0.50	-0.79	-1.004	-2.502	-1.317	-1.144	-1.026	-1.226	-1.057	-1.137	-1.040	-1.393	-1.151	-1.093
0.20	0.50	-0.91	-1.011	-2.501	-1.938	-1.600	-1.152	-1.789	-1.296	-1.577	-1.220	-2.034	-1.618	-1.437
0.10	0.50	-0.95	-1.022	-2.501	-2.304	-2.091	-1.465	-2.224	-1.743	-2.071	-1.611	-2.348	-2.106	-1.932
			S.E.											
1.00	0.00	-0.38	0.020	0.068	0.009	0.006	0.001	0.005	0.002	0.004	0.002	0.010	0.004	0.003
0.50	0.00	-0.61	0.041	0.043	0.017	0.011	0.003	0.009	0.005	0.007	0.004	0.018	0.008	0.005
0.20	0.00	-0.82	0.102	0.033	0.027	0.022	0.007	0.019	0.011	0.016	0.009	0.027	0.017	0.013
0.10	0.00	-0.90	0.204	0.031	0.029	0.028	0.013	0.026	0.019	0.024	0.017	0.028	0.025	0.021
1.00	0.50	-0.67	0.034	0.092	0.010	0.006	0.002	0.007	0.003	0.005	0.003	0.011	0.006	0.004
0.50	0.50	-0.79	0.069	0.052	0.017	0.012	0.004	0.013	0.007	0.010	0.006	0.019	0.011	0.008
0.20	0.50	-0.91	0.172	0.032	0.026	0.022	0.010	0.019	0.014	0.018	0.013	0.025	0.018	0.016
0.10	0.50	-0.95	0.344	0.028	0.027	0.027	0.017	0.018	0.019	0.019	0.018	0.025	0.019	0.019

Factor Model

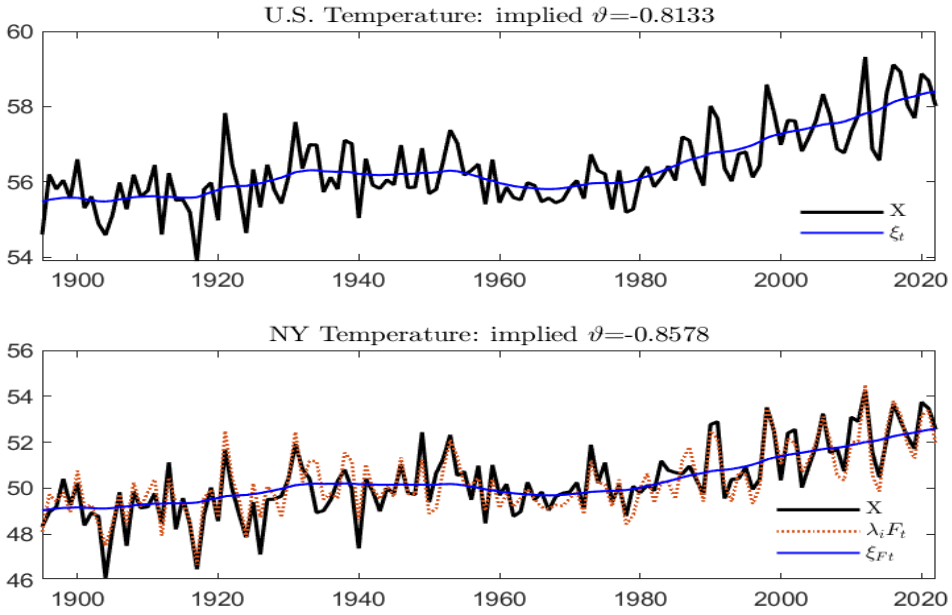
σ_λ	ρ	ϑ	Oracle		SN			SN-CA		SN-PA		$LD_K(T_0, T_2, m)$		
			$\hat{\beta}^*_\mu$	$\hat{\beta}^*_w$	T_1	T	$1:T$	$T_0 \pm k$	$T_2 \pm k$	$T_0 : T_1$	$T_1 : T_2$	$m = 0$	$m = 4$	$m = 9$
1.00	0.00	-0.38	-1.001	-2.503	-1.072	-1.029	-1.002	-1.019	-1.004	-1.011	-1.003	-1.094	-1.012	-1.007
0.50	0.00	-0.61	-1.003	-2.501	-1.251	-1.111	-1.007	-1.074	-1.017	-1.042	-1.011	-1.316	-1.048	-1.027
0.20	0.00	-0.82	-1.007	-2.500	-1.834	-1.500	-1.042	-1.368	-1.101	-1.230	-1.066	-1.937	-1.256	-1.151
0.10	0.00	-0.90	-1.013	-2.500	-2.251	-1.999	-1.156	-1.848	-1.336	-1.629	-1.233	-2.304	-1.677	-1.463
1.00	0.50	-0.67	-1.002	-2.505	-1.094	-1.039	-1.007	-1.064	-1.015	-1.037	-1.010	-1.122	-1.041	-1.024
0.50	0.50	-0.79	-1.004	-2.502	-1.317	-1.144	-1.026	-1.226	-1.057	-1.137	-1.040	-1.393	-1.151	-1.093
0.20	0.50	-0.91	-1.011	-2.501	-1.938	-1.600	-1.152	-1.789	-1.296	-1.577	-1.220	-2.034	-1.618	-1.437
0.10	0.50	-0.95	-1.022	-2.501	-2.304	-2.091	-1.465	-2.224	-1.743	-2.071	-1.611	-2.348	-2.106	-1.932
			S.E.											
1.00	0.00	-0.38	0.020	0.068	0.009	0.006	0.001	0.005	0.002	0.004	0.002	0.010	0.004	0.003
0.50	0.00	-0.61	0.041	0.043	0.017	0.011	0.003	0.009	0.005	0.007	0.004	0.018	0.008	0.005
0.20	0.00	-0.82	0.102	0.033	0.027	0.022	0.007	0.019	0.011	0.016	0.009	0.027	0.017	0.013
0.10	0.00	-0.90	0.204	0.031	0.029	0.028	0.013	0.026	0.019	0.024	0.017	0.028	0.025	0.021
1.00	0.50	-0.67	0.034	0.092	0.010	0.006	0.002	0.007	0.003	0.005	0.003	0.011	0.006	0.004
0.50	0.50	-0.79	0.069	0.052	0.017	0.012	0.004	0.013	0.007	0.010	0.006	0.019	0.011	0.008
0.20	0.50	-0.91	0.172	0.032	0.026	0.022	0.010	0.019	0.014	0.018	0.013	0.025	0.018	0.016
0.10	0.50	-0.95	0.344	0.028	0.027	0.027	0.017	0.018	0.019	0.019	0.018	0.025	0.019	0.019

Table 5: Dynamic System: SN Regressions in Averaged Data

$(T, S, N) = (50, 50, 50)$

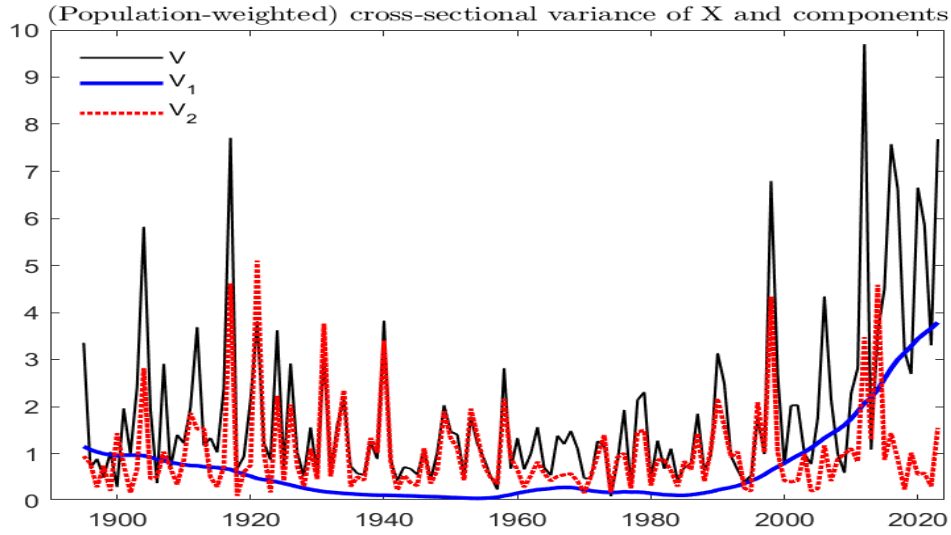
					SN-ADL(1,1)				SN-System		
ρ	α	κ	$\theta^{\dagger}$	θ^{*}	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\alpha}$	$\hat{\theta}^{\dagger}$	$\hat{\rho}$	$\hat{\kappa}$	$\hat{\theta}^{*}$
0.0	0.0	0.0	-1.5	-1.5	-0.999	-0.499	0.001	-1.500	-0.002	-0.000	-1.499
0.5	0.0	0.0	-1.5	-3.0	-0.999	-0.500	0.001	-1.500	0.498	-0.001	-3.000
0.8	0.0	0.0	-1.5	-7.5	-0.999	-0.501	0.001	-1.500	0.798	-0.001	-7.523
0.9	0.0	0.0	-1.5	-15.0	-0.999	-0.501	0.000	-1.500	0.898	-0.001	-15.124
1.0	0.0	0.0	-1.5	-Inf	-0.999	-0.501	0.000	-1.500	0.988	-0.001	-297.584
0.0	0.0	0.1	-1.5	-1.3	-0.999	-0.499	0.001	-1.500	-0.001	0.100	-1.303
0.5	0.0	0.1	-1.5	-2.3	-0.999	-0.500	0.001	-1.500	0.498	0.099	-2.307
0.8	0.0	0.1	-1.5	-4.3	-0.999	-0.501	0.001	-1.500	0.798	0.099	-4.289
0.9	0.0	0.1	-1.5	-6.0	-0.999	-0.501	0.000	-1.500	0.898	0.099	-6.011
1.0	0.0	0.1	-1.5	-10.0	-0.999	-0.501	0.000	-1.500	0.988	0.099	-9.451
0.0	0.5	0.0	-3.0	-3.0	-0.999	-0.500	0.501	-3.002	-0.001	-0.000	-3.002
0.5	0.5	0.0	-3.0	-6.0	-0.999	-0.500	0.500	-3.002	0.498	-0.001	-6.013
0.8	0.5	0.0	-3.0	-15.0	-0.999	-0.501	0.500	-3.001	0.798	-0.001	-15.086
0.9	0.5	0.0	-3.0	-30.0	-0.999	-0.501	0.500	-3.000	0.898	-0.001	-30.339
1.0	0.5	0.0	-3.0	-Inf	-0.999	-0.501	0.500	-3.000	0.990	-0.000	-473.554
0.0	0.5	0.1	-3.0	-2.3	-0.999	-0.500	0.500	-3.002	-0.001	0.100	-2.308
0.5	0.5	0.1	-3.0	-3.8	-0.999	-0.500	0.500	-3.002	0.498	0.100	-3.753
0.8	0.5	0.1	-3.0	-6.0	-0.999	-0.500	0.500	-3.002	0.798	0.099	-6.010
0.9	0.5	0.1	-3.0	-7.5	-0.999	-0.501	0.500	-3.002	0.898	0.099	-7.515
1.0	0.5	0.1	-3.0	-10.0	-0.999	-0.501	0.500	-3.001	0.990	0.099	-9.769
med. se SN(T)					0.020	0.030	0.016	0.023	0.024	0.016	0.384
med. se SN(5)					0.021	0.033	0.016	0.032	0.025	0.016	0.440

Figure 1: U.S. Annual Temperature Data



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Figure 2: Fanning Out of Cross-Section Variance in x and its Components



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