Online Appendices for

Heterogeneity in the Effect of Common Shocks on Health Care Expenditure Growth

Katharina Hauck[a] and Xiaohui Zhang*[b]
[a]School of Public Health, Imperial College London, UK
[b] School of Management and Governance, Murdoch University, Perth, Australia
* corresponding author

Appendix I Background

What if all heterogeneity in the effects of common shocks was observable?

If this was the case, then the problem could be solved -or at least alleviated- by a specification that includes interactions terms between the observable regressors and time, and that allows for time-varying slope coefficients, as for example proposed by Chernew and Newhouse (2011). However, the literature finds that a substantial proportion of differences in the spread of technology, and other common shocks, is due to factors that are either unobservable altogether, or unobserved in the country level data that are typically used by studies on HCE growth (McClellan and Kessler, 1999; Lyttkens, 2001; Packer et al., 2006; Hashimoto et al., 2006; Greenhalgh et al., 2008). If this is the case, then changes in unmeasured factors may cause the observed relationship between covariates and spending to change over time. As a result, heterogeneity in the impact of latent common factors on HCE growth in countries introduces cross-section dependence, endogeneity and correlation between year fixed effects and regressors. This may lead to inconsistent estimates and erroneous inference on the importance of observable drivers of expenditure growth, a problem that cannot be eliminated with interaction terms and time-varying slopes. The factor structure can capture any contemporaneous correlation that arises from the common response of countries to such unanticipated events, and recognize that there is cross-country dependence in HCE, caused by unobservable common factors in specific time periods.

Appendix II Methods

A. Multiple Imputation

MI proceeds in three steps: (1) generate *M* imputations (completed data sets); (2) conduct desired analysis on each imputation separately; (3) combine results obtained from the second step for each completed data set into a single multiple-imputation result(Rubin, 1987, Kenward and Carpenter, 2007, Horton and Lipsitz, 2001). We use predictive mean matching using three nearest neighbours and M=50 imputed datasets, following White et al. (2011). This method fills in multiple variables iteratively using a sequence of univariate imputation methods with fully conditional specification of prediction equations. It accommodates arbitrary missing value patterns, and it allows us to include country and year dummies and utilise robust standard errors. Summary statistics for two imputed data sets and all imputed variables are presented in Table III in the main body of the paper. In Figure A1 we plot overlay kernel densities of original and imputed data for six robust variables with highest proportions of missing values (ranging from 49.83% to 32.89%). Comparing the summary statistics of the imputed variables with the original ones in Table II, and the estimated kernel densities, we are reasonably confident that the imputations can be used for further analysis. Table AI presents results from the model with variables having less than 25% missing values, compared with results from our main model with variables having less than 50% missing values. The similarity between these two sets of results further demonstrates the quality of our imputed data for variables with less than 50% missing values.

For each imputed data-set, we estimate the common factor model in different specifications. Let $\hat{\boldsymbol{\beta}}_m^r$ represent the estimated parameters from common factor model with specification M_r ($r = 1, 2, ..., 2^K$) by using the *m*-th ($m = 1, 2, ..., M$) imputed data set. Let $\left\{(\hat{\boldsymbol{\beta}}_m^r, \hat{\boldsymbol{U}}_m^r) : m = 1, 2, ..., M\right\}$ be the completed-data point estimates and variance-covariance estimates of $\boldsymbol{\beta}^r$ from M imputed datasets. For M_r, the MI point estimation of $\boldsymbol{\beta}^r$ is given as

$$\hat{\boldsymbol{\beta}}^r = \frac{1}{M}\sum_{m=1}^{M}\hat{\boldsymbol{\beta}}_m^r , \qquad \text{(A-1)}$$

and the MI variance-covariance estimate is

$$Var(\hat{\boldsymbol{\beta}}^r) = M^{-1}\sum_{m=1}^{M}\hat{\mathrm{U}}_m^r + (1+M^{-1})\sum_{m=1}^{M}(\hat{\boldsymbol{\beta}}_m^r - \hat{\boldsymbol{\beta}}^r)(\hat{\boldsymbol{\beta}}_m^r - \hat{\boldsymbol{\beta}}^r)' / (M-1) . \qquad \text{(A-2)}$$

B. Bayesian Model Averaging

Most studies that use Bayesian Model Averaging (BMA) to identify determinants of economic growth at country level are based on cross-sectional models.[1] Let $\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon}$ represent a generic regression model of health care expenditure growth ($\boldsymbol{y}$) on a set of growth determinants ($\boldsymbol{X}$). Given the large number of potential growth determinants, there potentially exist an enormous amount of empirical models when the empirical researcher seeks to explore different combination of determinants. Suppose we have *K* potential determinants, we then would have a maximum of 2^K possible combinations of regressors, i.e. 2^K different models to estimate. Let M_r ($r = 1, 2, ..., 2^K$) denote the *r*th model under consideration, then M_r depends on

1 To the best knowledge of authors, the only one exception is Moral-Benito (2012).

a set of growth determinants, $\boldsymbol{X}^r$, and their corresponding coefficients β^r. By Bayes' rule in densities, the *posterior density* for β^r under model M_r is written as

$$p(\boldsymbol{\beta}^r \mid \boldsymbol{y}, M_r) = \frac{f(\boldsymbol{y} \mid \boldsymbol{\beta}^r, M_r)\, p(\boldsymbol{\beta}^r \mid M_r)}{f(\boldsymbol{y} \mid M_r)}, \quad \text{(A-3)}$$

where $p(\boldsymbol{\beta}^r \mid M_r)$ is the *prior density* of β^r; $f(\boldsymbol{y} \mid \boldsymbol{\beta}^r, M_r)$ denotes likelihood of $\boldsymbol{y}$ given β^r under model M_r; and $f(\boldsymbol{y} \mid M_r)$ is the *prior density* of $\boldsymbol{y}$.

Using Bayes' rule, the posterior probability, $p(M_r \mid \boldsymbol{y})$ for $r = 1, 2, ..., 2^K$, can be obtained as

$$p(M_r \mid \boldsymbol{y}) = \frac{f(\boldsymbol{y} \mid M_r)\, p(M_r)}{f(\boldsymbol{y})}, \quad \text{(A-4)}$$

which can be used to assess the degree of support for M_r. The prior density of M_r, i.e. $p(M_r)$, measures how likely we believe M_r to be the correct model concerning the relative likelihood of all possible models before considering the data. $f(\boldsymbol{y} \mid M_r)$ is the marginal likelihood and is calculated by integrating both sides of Equation (A-1) with respect to β^r. Use the fact that $\int p(\boldsymbol{\beta}^r \mid \boldsymbol{y}, M_r)\, d\boldsymbol{\beta}^r = 1$, we get

$$f(\boldsymbol{y} \mid M_r) = \int f(\boldsymbol{y} \mid \boldsymbol{\beta}^r, M_r)\, p(\boldsymbol{\beta}^r \mid M_r) d\boldsymbol{\beta}^r. \quad \text{(A-5)}$$

Let $\boldsymbol{\beta}$ be a vector of parameters that has a common interpretation in all models, i.e. $\boldsymbol{\beta}$ is function of β^r for each $r = 1, 2, ..., 2^K$. According to the rules of probabilities, we can calculate the posterior density of the parameters for all the models under consideration as

$$p(\boldsymbol{\beta} \mid \boldsymbol{y}) = \sum_{r=1}^{2^K} p(M_r \mid \boldsymbol{y})\, p(\boldsymbol{\beta} \mid \boldsymbol{y}, M_r). \quad \text{(A-6)}$$

Follow Raftery (1995) and Sala-i-Martin et al. (2004), the posterior probability of model M_r is

$$p(M_r \mid \boldsymbol{y}) = \frac{p(M_r)(NT)^{-k^r/2} SSE_r^{-NT/2}}{\sum_{j=1}^{2^K} p(M_j)(NT)^{-k^j/2} SSE_j^{-NT/2}}, \quad \text{(A-7)}$$

where *NT* is the number of observations, k^r is the number of regressors included in model M_r, and SSE_r is the sum of squared residuals from the *r*th regression model of M_r.

Regarding the specification of prior probabilities attached to different models, $p(M_r)$, a common practice is to assign equal prior probability to each model. This however has troubling implications when the number of models under consideration is large. In particular it implies a very strong prior belief that the number of regressors included in the true model is very large, with expected model size equal to $K/2$. Instead of choosing prior probabilities for different models, we specify a prior mean model size, $\bar{k}$. Each variable has the same prior probability, i.e. $\bar{k}/K$, of being included, and the probability is independent of the inclusion of any other variables. In our empirical analysis, we choose $\bar{k} = 7$ but also compare results to $\bar{k} = 5, 9, 11$, and 16. Results are presented in Table AII. We find that different prior assumptions about the model size have no practical impact on the results.

Table AI Results Comparison between Model with Variables Less than 25% Missing Values and Model with Variables Less than 50% Missing Values

	25% data set					**50% data set**			
	Posterior Mean	**Posterior Standard Deviation**	**Sign Certainty Probability**	**Fraction of Regressions with |tstat|>2**		**Posterior Mean**	**Posterior Standard Deviation**	**Sign Certainty Probability**	**Fraction of Regressions with |tstat|>2**
lngdp	0.2328	0.0538	0.9999	0.9997	**psss**	-0.8086	0.1746	1.0000	1.0000
ppuhe	-0.2387	0.0591	0.9998	0.9999	**lnins**	0.2220	0.0556	1.0000	1.0000
ppop6	2.8224	0.9707	0.9974	0.9885	**punem**	-0.7289	0.1779	0.9998	0.9995
hcspc	2.3498	1.0479	0.9878	0.9633	**lnpha**	0.1537	0.0408	0.9997	0.9987
capit	2.3523	1.1956	0.9870	0.9586	**ppins**	-1.3837	0.6674	0.9982	0.9987
pcanm	0.0395	0.0198	0.9749	0.7406	**lngdp**	0.2329	0.0814	0.9955	0.9710
lnacc	0.0328	0.0176	0.9599	0.8348	**lnta**	0.0196	0.0071	0.9953	0.9884
lnmt	0.0556	0.0340	0.9430	0.5418	**ppop6**	3.0026	1.1341	0.9932	0.9413
pcove	0.1593	0.1003	0.9381	0.3510	**lninp**	0.1324	0.0566	0.9891	0.9202
lnalc	0.0297	0.0198	0.9222	0.6880	**pedx**	0.7309	0.3136	0.9883	0.8765
free	1.6467	1.3316	0.8896	0.8553	**hcspc**	2.2973	1.0279	0.9815	0.8957
lnle	-0.0898	0.0878	0.8499	0.4086	**ptexm**	-0.1617	0.0802	0.9719	0.7905
ffsa	0.8481	1.3688	0.7464	0.7219	**capit**	1.9228	1.0495	0.9700	0.8720
mixgp	-1.0128	1.4891	0.7439	0.7596	**lnbsi**	0.0954	0.0507	0.9659	0.5511
pgp1	0.0374	0.0932	0.6831	0.0817	**pgsh**	0.1626	0.0916	0.9658	0.5331
ppop8	0.8437	1.7712	0.6784	0.1911	**lntob**	0.0408	0.0225	0.9619	0.4578
pbirt	0.1575	0.4200	0.6527	0.0158	free	2.0821	1.2034	0.9466	0.8462
copay	0.3029	0.9839	0.6354	0.7285	pcove	0.1381	0.0924	0.9352	0.3823
mic	-0.4010	1.1472	0.6222	0.6614	lnacc	0.0279	0.0182	0.9302	0.6741
lndp	-0.0816	0.3803	0.5864	0.5725	lnger	0.0464	0.0311	0.9272	0.3998
caseh	-0.0685	0.7267	0.5460	0.6362	lnalc	0.0405	0.0276	0.9259	0.6197
globu	-0.0490	0.7244	0.5095	0.5468	lnlos	0.0414	0.0369	0.8665	0.0092
gatek	-0.0290	1.1909	0.5066	0.6947	pcanm	0.0302	0.0280	0.8565	0.2844
ws	0.1718	1.5871	0.5029	0.7213	lngp	-3.4639	3.3829	0.8447	0.0225
					ppuhe	-0.1654	0.1943	0.8305	0.9144
					pbirt	0.3712	0.4201	0.8160	0.1461
					lnmt	0.0354	0.0467	0.7785	0.2288
					ffsa	0.7351	1.0853	0.7647	0.4335
					gatek	0.6901	1.0820	0.7477	0.5585
					ppop8	1.2950	2.0916	0.7329	0.3116
					copay	0.4658	0.8625	0.7227	0.4604
					lnle	-0.0506	0.0971	0.6999	0.0948
					mic	0.4111	1.0973	0.6677	0.4513
					phemp	0.1066	0.3747	0.6107	0.0000
					ws	-0.1969	1.2775	0.6002	0.3670
					pgp1	0.0169	0.1001	0.5955	0.0243
					pfpr	0.0002	0.0023	0.5776	0.2825
					lndp	-0.0779	0.3980	0.5729	0.1916
					globu	0.0429	0.6771	0.5430	0.2363
					lndoc	0.0011	0.0188	0.5226	0.0002
					mixgp	-0.1451	1.3140	0.5214	0.3657
					caseh	0.0243	0.7701	0.5142	0.3368
					lnhospc	-0.0004	0.0268	0.5004	0.0000

Table AII Results Comparison across Models with Different Prior Mean Model Size

	$\bar{k}=5$		$\bar{k}=7$		$\bar{k}=9$		$\bar{k}=11$		$\bar{k}=16$	
	Posterior Mean	**Sign Certainty Probability**	**Posterior Mean**	**Sign Certainty Probability**	**Posterior Mean**	**Sign Certainty Probability**	**Posterior Mean**	**Sign Certainty Probability**	**Posterior Mean**	**Sign Certainty Probability**
psss	-0.7861	1.0000	-0.8086	1.0000	-0.8291	1.0000	-0.8288	1.0000	-0.8288	1.0000
lnins	0.2136	1.0000	0.2220	1.0000	0.2295	1.0000	0.2293	1.0000	0.2295	1.0000
punem	-0.7654	1.0000	-0.7289	0.9998	-0.6904	0.9992	-0.6898	0.9992	-0.6902	0.9992
lnpha	0.1592	0.9999	0.1537	0.9997	0.1496	0.9992	0.1494	0.9992	0.1495	0.9992
ppins	-1.2681	0.9985	-1.3837	0.9982	-1.4929	0.9977	-1.4901	0.9977	-1.4946	0.9978
lngdp	0.2659	0.9992	0.2329	0.9955	0.2013	0.9843	0.2008	0.9843	0.2011	0.9844
lnta	0.0203	0.9970	0.0196	0.9953	0.0189	0.9924	0.0190	0.9924	0.0189	0.9924
ppop6	3.2836	0.9974	3.0026	0.9932	2.8363	0.9856	2.8347	0.9856	2.8315	0.9853
lninp	0.1377	0.9932	0.1324	0.9891	0.1286	0.9839	0.1284	0.9838	0.1285	0.9840
pedx	0.7218	0.9906	0.7309	0.9883	0.7347	0.9854	0.7352	0.9854	0.7346	0.9853
hcspc	2.4034	0.9895	2.2973	0.9815	2.2720	0.9722	2.2753	0.9723	2.2688	0.9723
ptexm	-0.1641	0.9796	-0.1617	0.9719	-0.1585	0.9627	-0.1584	0.9625	-0.1583	0.9622
capit	1.9589	0.9844	1.9228	0.9700	1.8817	0.9490	1.8865	0.9493	1.8812	0.9486
lnbsi	0.0965	0.9740	0.0954	0.9659	0.0926	0.9537	0.0926	0.9535	0.0925	0.9536
pgsh	0.1493	0.9599	0.1626	0.9658	0.1735	0.9691	0.1735	0.9692	0.1732	0.9690
lntob	0.0422	0.9714	0.0408	0.9619	0.0390	0.9492	0.0390	0.9491	0.0390	0.9492
free	2.3624	0.9801	2.0821	0.9466	1.8032	0.8995	1.8065	0.9000	1.8022	0.8995
pcove	0.1398	0.9517	0.1381	0.9352	0.1384	0.9189	0.1386	0.9189	0.1386	0.9191
lnacc	0.0291	0.9525	0.0279	0.9302	0.0271	0.9091	0.0272	0.9097	0.0273	0.9106
lnger	0.0527	0.9547	0.0464	0.9272	0.0419	0.9000	0.0420	0.9002	0.0420	0.9002
lnalc	0.0452	0.9652	0.0405	0.9259	0.0357	0.8754	0.0358	0.8764	0.0356	0.8745
lnlos	0.0409	0.8742	0.0414	0.8665	0.0414	0.8559	0.0414	0.8561	0.0414	0.8558
pcanm	0.0289	0.8723	0.0302	0.8565	0.0309	0.8392	0.0310	0.8395	0.0310	0.8401
lngp	-3.6329	0.8691	-3.4639	0.8447	-3.3554	0.8242	-3.3502	0.8244	-3.3571	0.8244
ppuhe	-0.1768	0.8761	-0.1654	0.8305	-0.1555	0.7865	-0.1573	0.7906	-0.1571	0.7890
pbirt	0.3802	0.8544	0.3712	0.8160	0.3561	0.7801	0.3551	0.7793	0.3560	0.7801
lnmt	0.0322	0.7693	0.0354	0.7785	0.0347	0.7560	0.0349	0.7577	0.0348	0.7573
ffsa	0.7326	0.8048	0.7351	0.7647	0.7452	0.7376	0.7430	0.7364	0.7503	0.7389
gatek	0.9037	0.8166	0.6901	0.7477	0.5349	0.6898	0.5352	0.6901	0.5399	0.6917
ppop8	1.9168	0.8181	1.2950	0.7329	0.8622	0.6605	0.8630	0.6606	0.8622	0.6605
copay	0.6712	0.8107	0.4658	0.7227	0.3047	0.6492	0.3008	0.6472	0.3003	0.6479
lnle	-0.0214	0.5985	-0.0506	0.6999	-0.0728	0.7542	-0.0730	0.7557	-0.0719	0.7525
mic	0.8145	0.7846	0.4111	0.6677	0.1090	0.5653	0.1018	0.5618	0.1071	0.5638
phemp	0.0961	0.6026	0.1066	0.6107	0.1157	0.6166	0.1162	0.6170	0.1155	0.6164
ws	-0.2852	0.6483	-0.1969	0.6002	-0.0468	0.5489	-0.0459	0.5482	-0.0510	0.5493
pgp1	0.0278	0.6506	0.0169	0.5955	0.0088	0.5583	0.0088	0.5587	0.0091	0.5596
pfpr	0.0010	0.7118	0.0002	0.5776	-0.0004	0.5331	-0.0004	0.5319	-0.0004	0.5342
lndp	-0.0024	0.5025	-0.0779	0.5729	-0.1425	0.6200	-0.1419	0.6196	-0.1429	0.6204
globu	0.1122	0.5852	0.0429	0.5430	-0.0378	0.5004	-0.0424	0.5028	-0.0412	0.5019
lndoc	0.0029	0.5635	0.0011	0.5226	-0.0002	0.5058	-0.0002	0.5053	-0.0002	0.5056
mixgp	0.1907	0.5884	-0.1451	0.5214	-0.4208	0.5954	-0.4243	0.5947	-0.4284	0.5978
caseh	0.1815	0.6026	0.0243	0.5142	-0.0595	0.5303	-0.0618	0.5317	-0.0618	0.5320
lnhospc	0.0024	0.5415	-0.0004	0.5004	-0.0045	0.5547	-0.0043	0.5531	-0.0044	0.5547

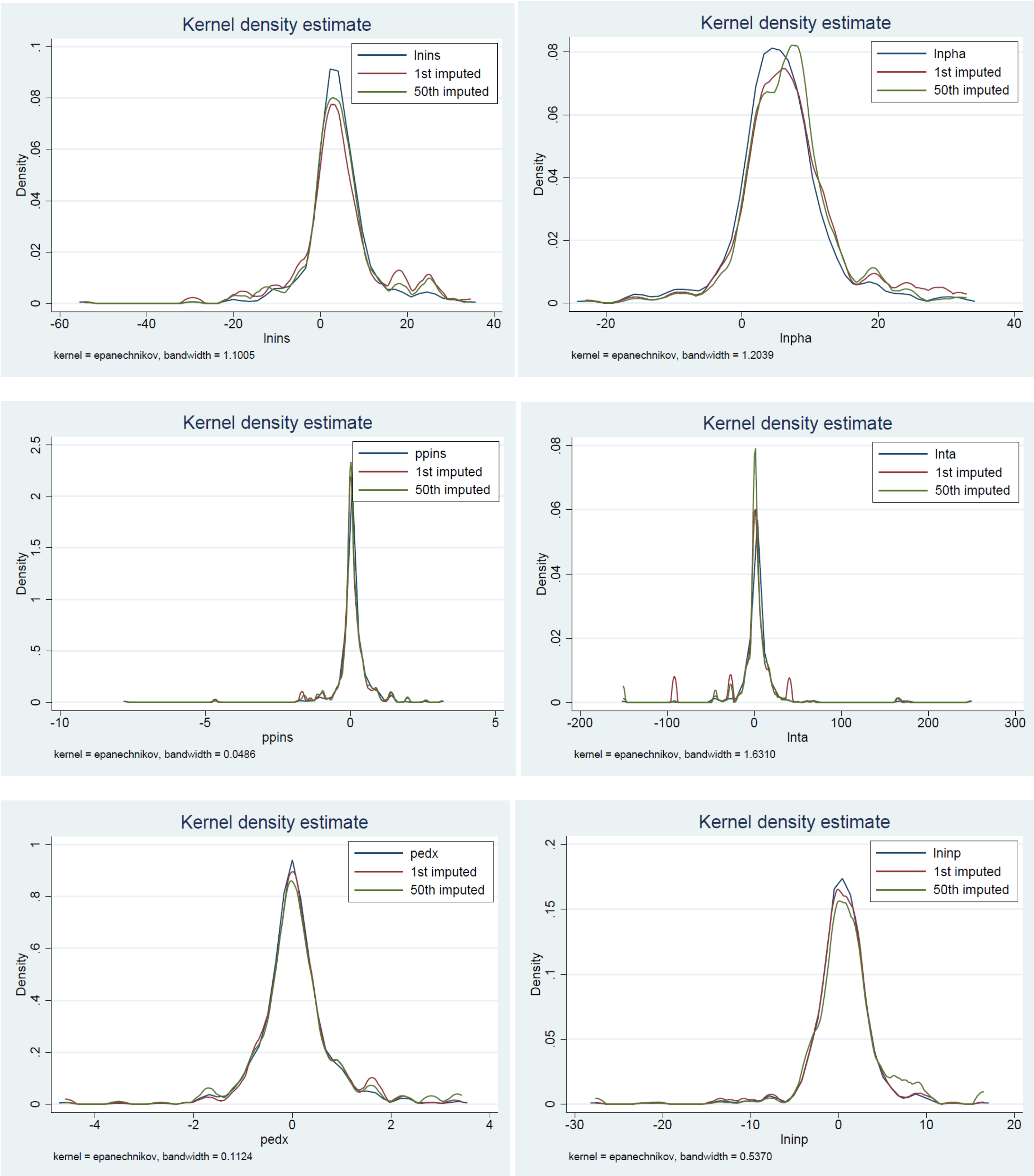

Figure A1 Estimated Kernel Densities of Observed Data and Imputed data for Six Robust Variables with Highest Proportions of Missing Values

References

CHERNEW, M. E. & NEWHOUSE, J. P. 2011. Chapter One - Health Care Spending Growth. *In:* MARK V. PAULY, T. G. M. & PEDRO, P. B. (eds.) *Handbook of Health Economics.* Elsevier.

GREENHALGH, T., ROBERT, G., BATE, P., MACFARLANE, F. & KYRIAKIDOU, O. 2008. *Diffusion of innovations in health service organisations: a systematic literature review*, Blackwell Publishing.

HASHIMOTO, H., NOGUCHI, H., HEIDENREICH, P., SAYNINA, O., MORELAND, A., MIYAZAKI, S., IKEDA, S., KANEKO, Y. & IKEGAMI, N. 2006. The diffusion of medical technology, local conditions, and technology re-invention: A comparative case study on coronary stenting. *Health Policy,* 79**,** 221-230.

HORTON, N. J. & LIPSITZ, S. R. 2001. Multiple Imputation in Practice. *The American Statistician,* 55**,** 244-254.

KENWARD, M. G. & CARPENTER, J. 2007. Multiple imputation: current perspectives. *Statistical Methods in Medical Research,* 16**,** 199-218.

LYTTKENS, C. H. 2001. Technological change around the world: evidence from heart attack care. *Health Affairs,* 20**,** 25-42.

MCCLELLAN, M. & KESSLER, D. 1999. A Global Analysis Of Technological Change In Health Care: The Case Of Heart Attacks. *Health Affairs,* 18**,** 250-255.

MORAL-BENITO, E. 2012. Determinants of economic growth: a Bayesian panel data approach. *Review of Economics and Statistics,* 94**,** 566-579.

PACKER, C., SIMPSON, S. & STEVENS, A. 2006. International diffusion of new health technologies: A ten-country analysis of six health technologies. *International Journal of Technology Assessment in Health Care,* 22**,** 419-428.

RAFTERY, A. E. 1995. Bayesian model selection in social research. *Sociological methodology,* 25**,** 111-164.

RUBIN, D. B. 1987. Multiple Imputation for Nonresponse in Surveys (Wiley Series in Probability and Statistics).

SALA-I-MARTIN, X., DOPPELHOFER, G. & MILLER, R. I. 2004. Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach. *American Economic Review,* 94**,** 813-835.

WHITE, I. R., ROYSTON, P. & WOOD, A. M. 2011. Multiple imputation using chained equations: issues and guidance for practice. *Statistics in Medicine,* 30**,** 377-399.