Using Panel VAR to Analyze International Knowledge Spillovers

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Abstract

Technology diffusion often plays a critical role in models of trade and economic growth. Most existing empirical tests for international technology spillovers suggest some role for spillovers in explaining productivity growth. It has been relatively difficult, however, to identify separate roles for the direct and indirect channels of knowledge spillovers. The influence of these channels is often confounded due to the focus on TFP and R&D spending within a cross section or panel data setting. This paper employs an alternative methodology to investigate the role of direct knowledge spillovers. Using citation weighted domestic patents, citation weighted foreign patents and value added for 14 US manufacturing industries over the period 1977-2004 a Panel VAR methodology is employed to investigate the dynamic role of direct and indirect knowledge spillovers. Evidence for the role of the direct knowledge spillovers channel is found - an increase in citation weighted patents abroad directly increases the measure of domestic citation weighted patents, after accounting for the influence of productivity/value added. The role of foreign innovative activity, however, is small relative to the role of US innovative activity in explaining the dynamics of industry value added.

Keywords: knowledge spillovers, patenting, productivity, panel VAR
JEL: O33; F43; C32; C33; L6

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1 Introduction

International technology spillovers play a potentially important role in economic growth and productivity/income convergence. Technology diffusion often plays a critical role in theoretical models of international trade and economic growth and economists' understanding of the relationship between trade, knowledge creation and growth. The literature recognizes roles for both direct channels and indirect channels of technological diffusion. Direct channels work through the direct benefits to researchers in one economy from knowledge generated abroad. The role of this channel is diminished to the degree that spillovers are geographically localized and/or the receiving economy lacks absorptive capacity to utilize the knowledge. Indirect channels for diffusion rely on trade, often in intermediate goods, and Foreign Direct Investment (FDI). It has been relatively difficult to identify separate roles for the direct and indirect channels of knowledge spillovers. The influence of these channels is often confounded due to the literature focus on TFP and R&D spending within a cross section or panel data setting. This paper employs an alternative methodology to identify the role of direct knowledge spillovers.

The evidence provided in this paper is of significant importance in formulating an understanding of trade, innovation and growth. Consider the extremes encountered in the literature. Eaton and Kortum (2001) provide a theoretical framework where technology transfer is limited by trade and therefore geographic distance. An implication of Eaton and Kortum is that foreign R&D and/or patents are reflected in TFP, but since the effect is indirect, there would be no impact on domestic R&D and/or patents. This view promotes the indirect channel of spillovers. In contrast, Howitt and Mayer-Foulkes (2005), Acemoglu, Aghion, and Zilibotti (2006) and Ertur and Koch (2011) promote a view that completely abstracts from trade and explains convergence in income growth rates via a direct spillover of knowledge across international borders, thus promoting the importance of the direct channel for spillovers. In this view convergence does not depend on openness or trade, but instead simply on the existence of innovator/entrepreneurs who actively engage in innovation, thus benefiting from the public goods nature of knowledge created internationally.

An empirical literature has developed and provides important insights into the role of knowledge/R&D spillovers. While each of the existing studies has relative strengths and weaknesses, they are each specified in a manner that makes it difficult to discern the role of the direct channel for spillovers. Despite the inability to identify the channels through which spillovers operate, this literature does provide evidence of a role for knowledge spillovers in general, conditional on absorptive capacity (in addition to the papers above see for example Coe and Helpman, 1995; Yang, 2003; Kugler, 2006; Lee, 2006; Belderbos, Ito, and Wakasugi, 2008; Mancusi, 2008; Hu and Jefferson, 2009; Coe, Helpman and Hoffmaister, 2009). Furthermore, it does seem clear that knowledge is geographically localized to a significant degree. Keller (2002), for example, estimates the impact of domestic and foreign R&D on TFP. The effectiveness of foreign R&D negatively depends on the bilateral geographic distance between the source and the recipient country. While this suggests that the role of direct knowledge spillovers in innovation and growth is limited by geography, it by no means rules out or subordinates a direct channel for knowledge transfer. On this issue Branstetter (2001) finds no evidence of international knowledge spillovers and argues that the explanation is the geographic concentration of knowledge. On the other hand, using a Dynamic OLS (DOLS) methodology, Lee (2006) reports significant evidence of direct knowledge spillovers. Eberhardt, Helmers and Strauss (2013) find evidence of knowledge spillovers and unobserved cross-sectional dependencies and argue that ignoring spillovers can lead to inflated estimates of private returns to R&D.

The existing literature, summarized below, is largely centered on methodologies that make use of panel data with fixed effects or time series models that do not take advantage of the potential benefits of constructing a longitudinal data set. The results of these studies confound direct and indirect channels for spillovers. The present paper looks at more disaggregated US manufacturing industries instead of national aggregates and provides a full analysis of the dynamics of spillovers by specifying a panel vector autoregression (PVAR) that is used to estimate the response of domestic innovation following an impulse in foreign patenting while controlling for the dynamics of value added, where the indirect channel operates, thus more accurately identifying the direct channel for knowledge spillovers. While no empirical methodology can completely overcome endogeneity and omitted variable problems problems, our Panel Vector Autoregression (PVAR) methodology and choice of domestic and foreign citation weighted patents, represent a significant methodological improvement. In the PVAR the variables are treated symmetrically in terms of endogeneity at the estimation stage. Furthermore, the influence of foreign patent activity, an output measure, on domestic patent activity, another output measure, is likely to be more direct and is likely to be influenced by fewer omitted variables. The present paper's methodology includes testing for cointegration, derivation of impulse responses, and calculating forecast error variance decompositions. We believe the panel VAR approach used in this paper is the preferred approach and represents a significant methodological improvement over existing empirical work in this area.[1]

The rest of the paper is organized as follows. Section 2 summarizes the related literature. Section 3 outlines the empirical methodology. Data construction and explanation of main variables are presented in Section 4. Section 5 provides the empirical analysis and results. Finally, Section 6 concludes.

2 Literature Overview

The empirical literature has stressed the importance of knowledge/R&D spillovers conditional on absorptive capacity using methodologies based on panel data with fixed effects or time series models and counfounding the direct and indirect channel of knowledge spillovers. Coe and Helpman (1995) estimate total factor productivity (TFP) in 22 OECD countries in the period of 1971-1990 as a function of domestic and foreign cumulative R&D, where the latter is weighted by trade partner import shares. Their paper was the first to highlight foreign R&D as a source of knowledge spillovers. Using micro level data on US and Japanese firms' patenting over the period of 1985-1989 and fixed effects panel methodology, Branstetter (2001) finds no evidence

[1] For a recent usage of panel VAR to study determinants of patents at the firm level see Blazsek and Escribano (2012).

of international knowledge spillovers and argues that knowledge is geographically concentrated. In contrast, Yang (2003) finds evidence of international knowledge spillovers in Taiwan by employing a fixed effects panel approach where domestic patents are regressed on foreign patents. However, the results of Yang might suffer from panel unit roots as the data set is only twice as wide as it is long. In a study of 10 Colombian industries, Kugler (2006) estimates the influence of inward FDI on TFP using time series techniques and finds evidence of inter-industry spillovers but not intra-industry spillovers. Nevertheless, the results are presented industry by industry and a panel data model is not used. Mancusi (2008) looks for evidence of international spillovers by regressing citation weighted patents from the European Patent Office as a function of domestic and foreign R&D and a measure of absorptive capacity. Mancusi finds strong evidence of spillovers from foreign R&D where absorptive capacity is high for laggard countries.

Using data for 16 OECD countries in the period of 1981-2000, Lee (2006) studies the effect of inward and outward FDI, intermediate goods imports and a disembodied "direct" channel on TFP. The direct channel is estimated through a measure of technological proximity and patent citations between countries. Lee (2006) finds that spillovers through inward FDI and direct channel are significant, while spillovers through outward FDI and imports of intermediate goods are not significant.[2] In addition to a focus on industry level data, our paper differs from Lee (2006) in several important respects. First, the results in Lee (2006) are based on pooled OLS/ DOLS with fixed effects. Therefore the dependant variable, productivity, is assumed to be the only endogenous variable in the analysis. Plausible channels of endogeneity exist for each variable on the right hand side of Lee's regression. Furthermore, any factor that influences productivity and is missing from the model specification potentially causes a bias in the estimated influence of the direct and indirect channels on productivity.

The next section outlines our empirical methodology and estimation strategy that provide methodological improvement to the existing literature.

[2] For inward FDI channels of knowledge transfer see also Belderbos, Ito and Wakasugi (2008), Bitzer and Kerekes (2008), Bitzer, Geishecker and Gorg (2008), and Hu and Jefferson (2009).

3 Empirical Methodology

As outlined above, existing empirical studies of knowledge spillovers confound the direct and indirect channels for international knowledge spillovers because they often rely on measures such as cumulative foreign and domestic R&D and their relationship to productivity. Furthermore, the process of knowledge creation, spillovers and productivity growth are dynamic in nature and, therefore, difficult to capture with cross sectional panel data methodologies that make use of wide but short panel data sets. A vast majority of existing studies are based on these methodologies.

The present research takes an alternative approach. In the past decade the Vector Auto Regression (VAR) methodology, attributed to Sims (1980), has been expanded to include panel data. It is now possible to model complex dynamics in a multivariate time series setting using panel data sets that are relatively narrow and long. In the initial estimation all variables are treated symmetrically in terms of endogeneity. Issues of Granger causality and stability are easily studied. Some structure must be imposed on the estimated reduced form model to recover structural parameters and investigate the dynamic relationships between the variables. In some cases there is little to guide the researcher when imposing the necessary restrictions. In other settings existing empirical and theoretical work can provide a strong case for imposing a particular set of identifying restrictions. That is the case in the present paper.

Rather than rely on input measures such as cumulative R&D we focus on the output of innovative activity, patents. Using R&D has a disadvantage, as the stochastic process of innovation is not captured. Furthermore, the return to R&D expenditures varies based on whether it is publicly funded or privately funded.[3] Focusing on patents allows to more specifically capture innovative activity over a longer time period. It is important to note that patents have their disadvantages as well, namely the fact that not all knowledge that is created is patented, but patents is the best measure to study knowledge spillovers in our setting. In addition, not all

[3] See Keller (2010) for a discussion of R&D, patents and productivity for studying knowledge spillovers and their advantages and disadvantages.

patents are equally valuable so we employ the now popular technique of weighting patents by their citation counts (Jaffe and Trajtenberg, 1992; Jaffe and de Rassenfosse, 2016). Citation weighted patents are collected by industry and are categorized by national origin as either US or foreign. To account for the role of the business cycle on R&D and to control for the indirect channel of knowledge spillovers we include industry real value added. Value added is essential as it controls for the dynamics related to the indirect channel for knowledge spillovers, the use of imported intermediate goods and their role in enhancing value added. Each variable in the Panel VAR is allowed to influence its own dynamics as well as the dynamics of all the other variables in the model. Thus, it is possible to evaluate the influence of foreign innovative activity on US innovative activity (and indeed vice versa) independent of the specific influence of foreign innovative activity on US value added. The role of indirect knowledge spillovers on value added through the importation of higher technology intermediate goods is captured by the dynamic relationship between foreign innovation and US value added independent of foreign innovation's influence on US innovation.

The literature outlined above suggests that value added is causally prior to both domestic and foreign innovative activity. It will take time for innovations to be implemented and impact value added, but value added will have an important contemporaneous impact on innovation since the existing literature strongly suggests that there is an R&D/innovation cycle that follows the business cycle (Walde and Woitek, 2004; Ouyang, 2011; Aghion, Askenazy, Berman, Cette, and Eymard, 2012). If innovations tend to be patented at home before they are patented abroad and knowledge spillovers are geographically localized and spread over time then foreign patenting activity in the US should be causally prior to US patenting activity in the US (Branstetter, 2001). This suggests a set of restrictions on the reduced form VAR that exactly identifies the parameters of the underlying structural model. The next section provides more detail concerning the construction of the data set. Section 5 provides the empirical analysis of US real value added, domestic citation weighted patents, and foreign citation weighted patents across 14 US manufacturing industries over the 28 year period from 1977 to 2004. Our total sample size is 392 observations in a fully balanced panel. While this is not as large a sample as used in many firm level studies, it is large enough to employ a panel VAR methodology. The panel is also balanced, and this makes it possible to conduct a set of panel cointegration tests.

4 Data

Data for all utility patents in the United States for the period 1976-2006 are obtained from the NBER patent data project (Hall, Jaffe and Trajtenberg 2001).[4] Application date as opposed to grant date is used to account for lags in granting of patents. In this data set, each patent has a current technology class and a subclass as of 2008. This is beneficial as the United States Patent and Trademark Office (USPTO) constantly revises the technology class, and having each patent classified based on a current class allows for a consistent analysis and comparison. Using each patent's current technology class and subclass as of 2008 and a concordance from USPTO, patents are matched to 21 unique manufacturing product fields based on the 2002 North American Industry Classification System (NAICS). Based on the patent's first-inventor residence, patents are classified as US or foreign. Further, the total number of US and foreign patents by application year and product field are calculated. Citation-weighted US and foreign patents by application year and product field are calculated using the number of citations each patent received from 1976-2006 multiplied by a truncation weight that corrects for the citation truncation. It is a multiplier that can be applied to the number of total citations to adjust for the fact that earlier patents had a longer span and therefore might have more citations. As described in Hall et al (2001), truncation weight for citations is estimated based on the patent's grant year and technology category using six field specific obsolescence-diffusion model with year and lag dummies. Measure of truncated citations is not accurate for the last couple of years in the sample, as two-three years is a short time to obtain a correct measure of citations. This necessitates a restriction of the analysis to 1976-2004.

[4] Although patent data for US is available beyond 2006, the citations data is not easily available. Therefore we are using patent and patent citation data from 1976-2006 available from the NBER Patent Data Project.

Data on manufacturing value added by industry in the period of 1977-2004 is downloaded from the United States Bureau of Economic Analysis (BEA). Data on value added in 1976 is missing for many industries, therefore the time period is further reduced to 1977-2004. Industry categories of value added in 1977-1997 are based on NAICS 2002 classification system, while industry categories in 1998-2004 are based on NAICS 2007 classification system. Using a concordance from BEA, these two time periods are consistently combined by aggregating several industries. Using the BEA chain-weighted GDP price deflator (2009 as the base year), value added is deflated to obtain real value added. To match data on patents with real value added further aggregation of industries is necessary, which reduces the number of industries from 21 patent fields to 14 industries (see Table A1 in the Appendix).[5]

The final data set is a balanced panel of real value added, domestic and foreign US patents and citation-weighted domestic and foreign US patents for 14 manufacturing industries for the period of 28 years (1977-2004). Summary statistics are available in Table 1.

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Real Value Added	392	1031.669	508.215	194.561	2759.531
Unweighted US Patents	392	3426.755	5650.229	26	40307
Unweighted Foreign Patents	392	3067.069	5205.933	8	37371
Weighted US Patents	392	50752.25	115727.4	27.080	961178.1
Weighted Foreign Patents	392	29489.9	61746.18	0	484808

Note: Real value added is deflated using BEA chain-weighted GDP price deflator. Unweighted US and foreign patents are raw number of domestic and foreign patents in the United States. Weighted US and foreign patents are weighted by the number of citations that each patent received, taking into account the truncation weight.

As we can see from this table, means of unweighted US and foreign patents are close at 3427 and 3067 accordingly. US citation weighted and foreign citation weighted patents have substantially higher means as expected. However, the mean of weighted US patents is much higher than the mean of weighted foreign patents, 50752 and 29489 accordingly. The standard deviation for both weighted US and weighted foreign patents also increases substantially

[5] The code for the matching of patents to NAICS industrial classification and subsequently matching to BEA industrial classification is available from authors upon request.

Table 2 Descriptive Statistics by Industry

Industry	Variable	Mean	Std.Dev.	Min	Max
Food,	Real Value Added	1647.219	255.481	1315.886	2098.263
Beverage,	Weighted US Patents	3299.365	1406.299	49.697	5178.832
Tobacco	Weighted Foreign Patents	1284.906	502.338	13.538	1974.926
Textiles,	Real Value Added	688.571	110.956	395.838	843.392
Apparel,	Weighted US Patents	7126.109	3379.718	281.481	13979.190
Leather	Weighted Foreign Patents	2952.904	1199.626	40.613	4635.442
Wood	Real Value Added	307.999	41.607	194.561	367.659
Products	Weighted US Patents	994.735	451.155	198.616	1867.634
	Weighted Foreign Patents	398.902	216.413	0.000	973.138
Paper,	Real Value Added	1070.506	149.841	817.263	1296.117
Printing	Weighted US Patents	5607.688	2756.754	107.817	10248.13
	Weighted Foreign Patents	2400.693	1113.790	0.000	4372.585
Chemicals	Real Value Added	1662.031	495.269	1109.555	2583.014
	Weighted US Patents	71958.040	34894.870	1292.722	161482
	Weighted Foreign Patents	37334.62	15794.730	610.552	73126.98
Plastics,	Real Value Added	1402.553	211.172	1016.297	1753.088
Rubber,	Weighted US Patents	30612.71	11707.12	1299.26	48856.89
Oth. Transp. Eqp.	Weighted Foreign Patents	19703.58	7594.005	1365.269	34400.3
Non-metalic	Real Value Added	432.656	60.195	303.715	541.597
Mineral	Weighted US Patents	9802.362	3805.178	374.427	16597.99
Products	Weighted Foreign Patents	6034.039	2477.692	278.798	10105.26
Primary	Real Value Added	647.515	171.402	455.710	1068.62
Metals	Weighted US Patents	2522.180	898.846	27.080	4093.911
	Weighted Foreign Patents	2291.783	846.884	7.590	3818.698
Fabricated	Real Value Added	1216.131	125.096	1012.710	1486.616
Metal	Weighted US Patents	29238	10259.610	1624.095	46504.410
Products	Weighted Foreign Patents	15805.590	5775.240	1168.871	25357.410
Machinery	Real Value Added	1256.190	128.301	1050.133	1484.898
	Weighted US Patents	77426.580	31353.550	5483.836	132857.700
	Weighted Foreign Patents	67302.960	27290.150	7863.572	115122.300
Computer,	Real Value Added	1590.826	520.709	779.261	2759.531
Electronic	Weighted US Patents	349655.200	283047.400	23547.650	961178.100
Products	Weighted Foreign Patents	190000.600	142325.600	19887.100	484808
Electr. Equipment,	Real Value Added	546.157	35.947	458.314	613.021
Appliances,	Weighted US Patents	45750.120	20910.050	7625.862	83238.300
Components	Weighted Foreign Patents	31516.040	17912.370	9062.338	65634.800
Motor Vehicles	Real Value Added	1178.784	302.958	676.416	1689.964
Trailers,	Weighted US Patents	14477.160	8819.624	3382.220	31824.880
Parts	Weighted Foreign Patents	16899.590	8543.569	3571.070	33830.340
Furniture,	Real Value Added	796.226	208.832	527.308	1136.183
Other	Weighted US Patents	62061.260	37635.230	2597.313	133752.500
Manufact.	Weighted Foreign Patents	18932.410	9624.425	711.702	40560.640

as compared to the standard deviation of the unweighted measures. Since the descriptive statistics above are for 14 manufacturing industries, there might be variation by industry. Descriptive statistics by industry are presented in Table 2. As the analysis is concentrated on citation weighted patents, only weighted US patents and weighted foreign patents are presented in Table 2.

As we expected, Table 2 shows that there is substantial variation in both value added and weighted US and foreign patents across industry. The highest numbers of weighted patents are in Computer and Electronic Products, Chemicals, and Electrical Equipment, Appliance and Components industries. In the empirical analysis, cross-industry differences are controlled for by the inclusion of the industry fixed effect.

5 Empirical Results

Since the data are annual time series, unit roots and non-stationarity are a concern. Figures 1 & 2 plot real value added (Value), citation weighted foreign patents (FPat), and citation weighted US patents (Pat) for each of the industries in the data set. Given the high number of patents in the Computer and Electronics industry and the Chemical industry these industries are plotted separately to maintain a readable scale for the plots of the variables in the other industries.

The graphs show clear and potentially deterministic trends in the Value variable across industries. The FPat and Pat variables tend to show a clear upward trend and a reversal in trend sometime in the 1990s, again the same pattern is clear across industries. This reversal in the trend is evident for both US citation weighted patents and foreign citation weighted patents.[6] In general the plots of all three variables across industries suggests the possibility of non-stationarity.

[6] We use patent application year and not grant year to account for the lags in granting of patents, but since NBER patent dataset lists only patents granted through 2006, some patents that were applied for in the last years of the dataset will not be part of our data. In addition, there was a slowdown in the patent granting process because of the backlog of the applications and policy issues in late 1990s and early 2000s which additionally contributed to the drop of patents in our dataset.

Figure 1 Time-Series Plots

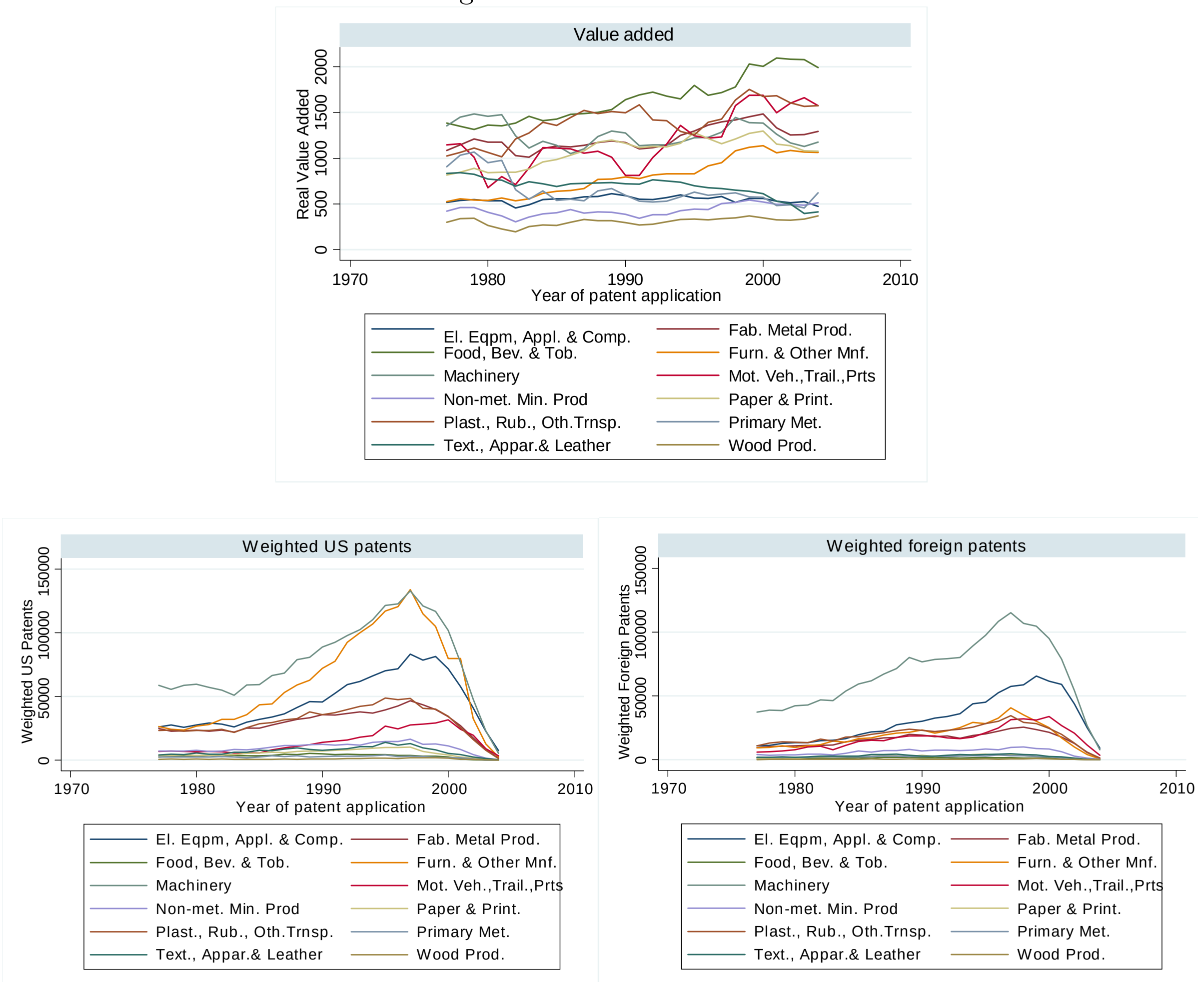
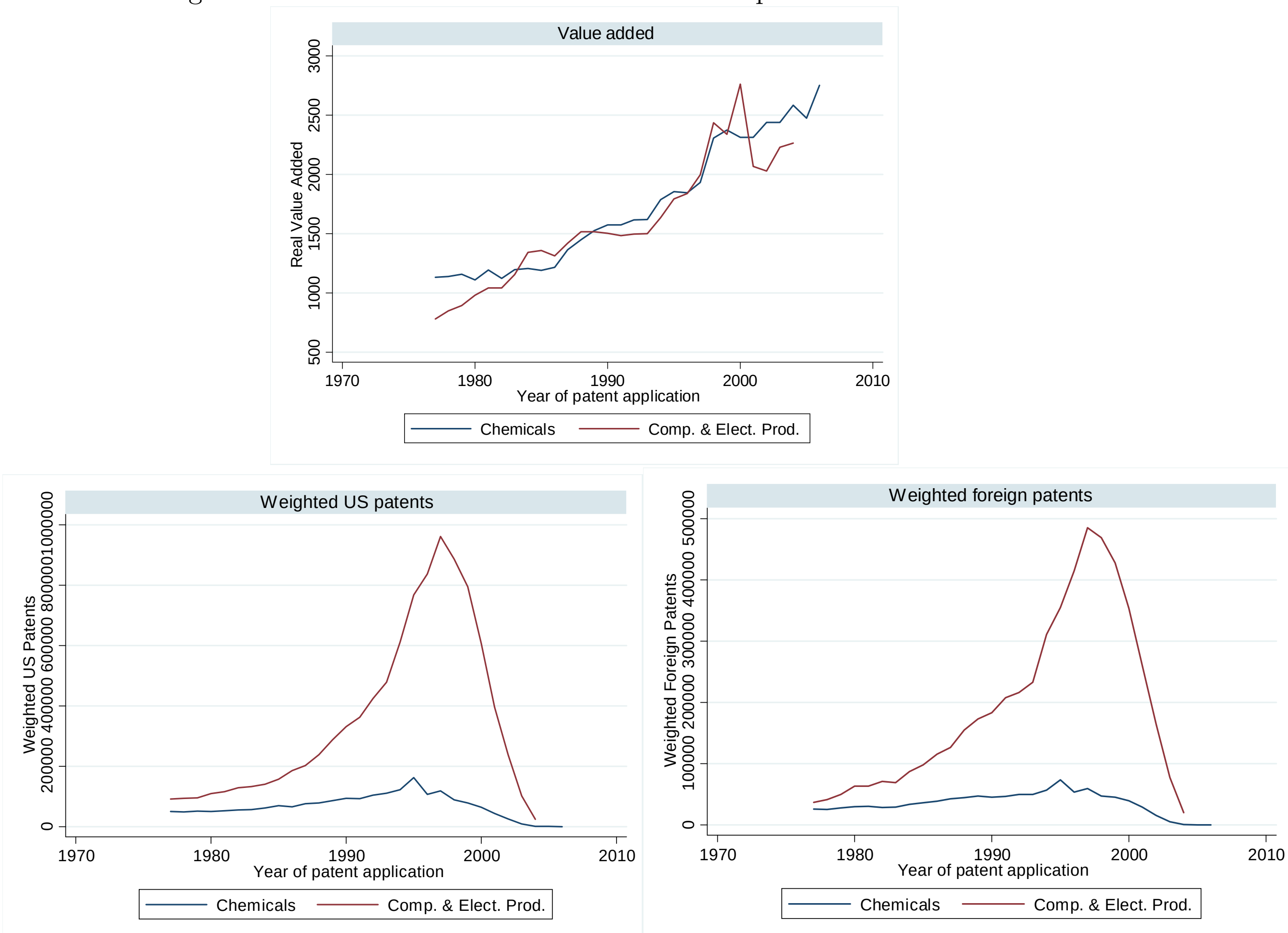


Figure 2 Time-Series Plots: Chemicals and Computers & Electronics



In formulating an approach to VAR construction, the information concerning the order of integration is essential. A VAR in first differences with an error correction term is appropriate if the levels of all variables contain a unit root and there exists a cointegrating vector between the variables in levels. If there is no cointegrating vector in levels and the differences of the variables are stationary a VAR in first differences is appropriate. Thus, we first test the order of integration for the levels and differences of the variables. Once we have established the order of integration for the variables we investigate the possibility of including an error correction term.

The first two rows of Table 3 show the results of the panel unit root tests for a full panel across all industries. The next two sets of results are based on a disaggregation of the full panel.

The panel unit root test is the PPerron panel unit root test. This test is appropriate for our data in the sense that the data is balanced and the number of cross sectional panels (N) are considered to be constant as T tends to infinity. The unit root tests of the level of Value, based on inspection of Figures 1 & 2, includes a time trend. All tests allow for panel specific intercepts.

Table 3 Panel Unit Root Tests

	Value	FPat	Pat	dValue	dFPat	dPat
All						
PP	23.4630	6.1900	3.4728	273.6319*	132.6447*	148.4292*
31&32						
PP	8.6281	2.5340	1.2093	95.8033*	94.6675*	90.4111*
33						
PP	11.0049	2.7957	1.7629	125.3746*	20.4936***	38.0888*

Note: PP is a PPerron panel unit root test. The test of the level of Value includes a trend term. ***indicates significance at 10% level. **indicates significance at 5% level. *indicates significance at 1% level.

The PP statistic tests the null hypothesis that all panels contain a unit root against the alternative that at least one is stationary. This test indicates unit roots across the levels of all three variables. This is evident when all industries are included in the panel and for the disaggregation of industries into two groups. We have 14 manufacturing industries in the sample. To look at a more disaggregated evidence of direct knowledge spillovers by industries, we split the sample into two groups- seven industries that comprise the aggregated 31 & 32 industries as one group, and the other seven industries of the aggregated industry 33. As we can see from table 2, there is substantial variation of patenting and value added across industries which motivated this disaggregation. Further evidence on differences between these two groups of industries is provided in the next section.

To test the order of integration for the variables, the 1st differences of the levels are tested for unit roots. These results are reported in columns (4) - (6) in Table 3. No evidence of non-stationarity is found in any of the panel unit root tests of the 1st differences, suggesting that the variables are integrated of order one, I(1). Figures 3 & 4 show the first differences of Value, FPat, and Pat.

Figure 3 Time-Series Plots of First-Differences

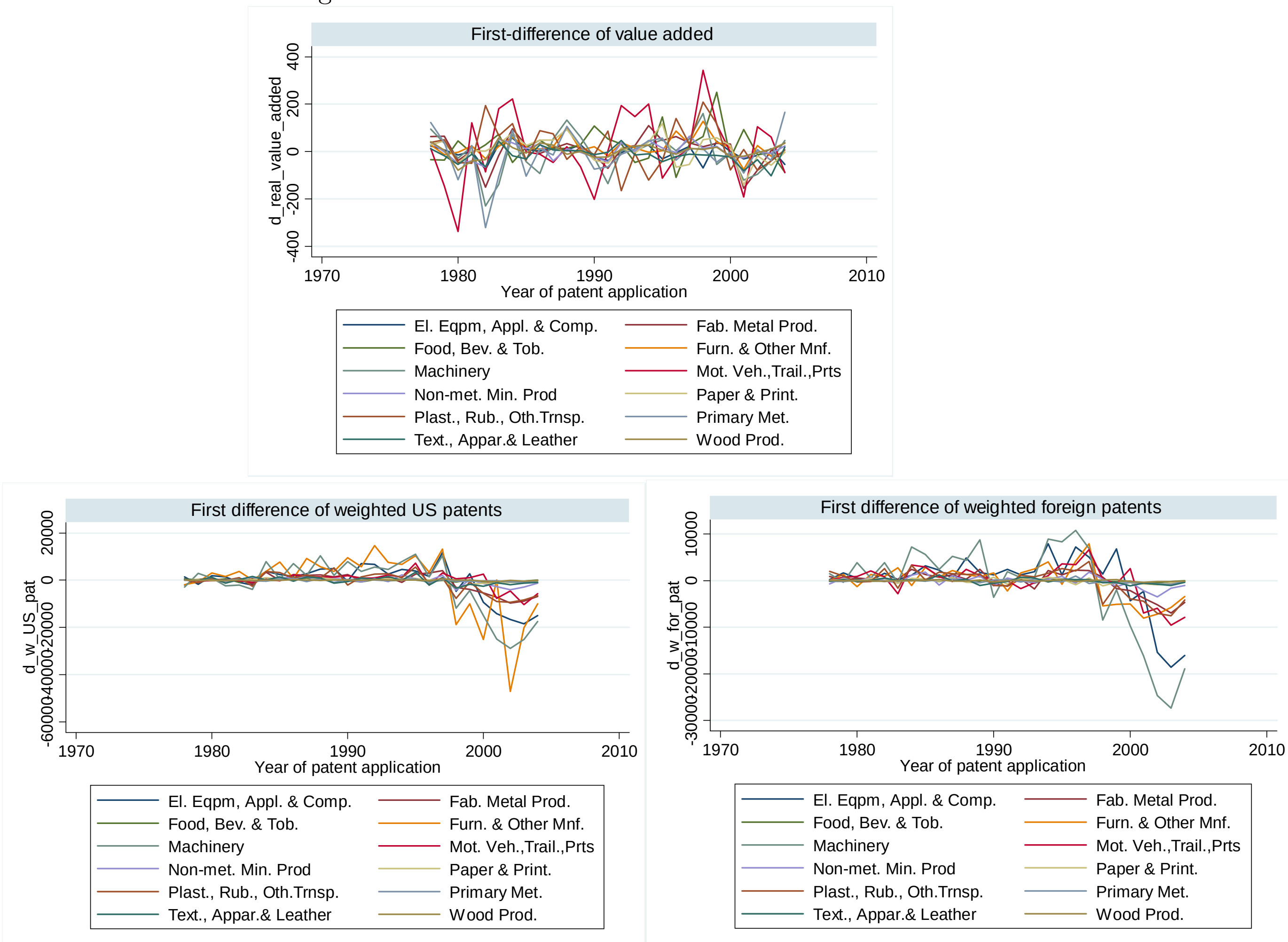
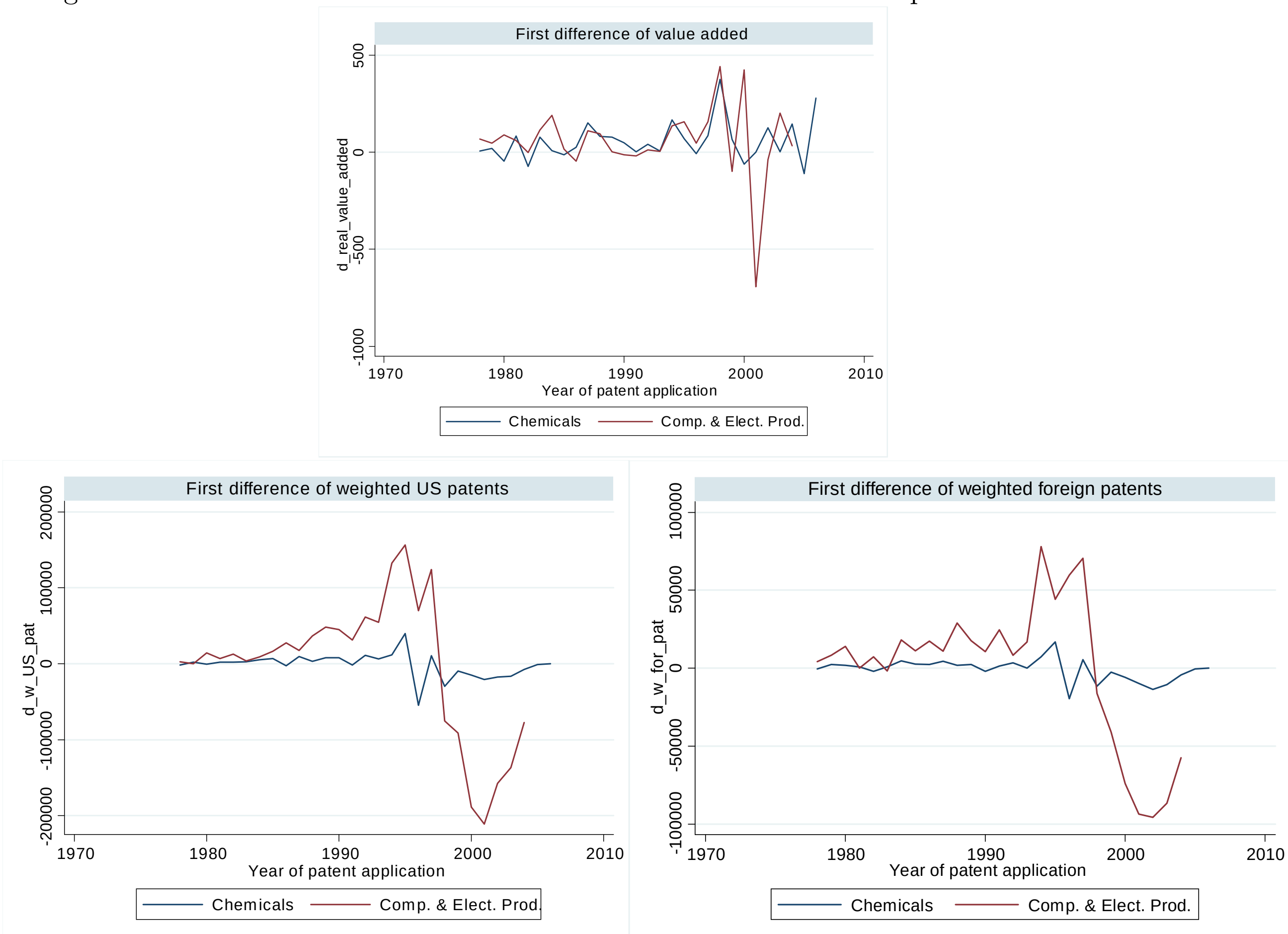


Figure 4: Time-Series Plots of First-Differences: Chemicals and Computers & Electronics



This information is of considerable importance in specifying an appropriate empirical model. Before concluding that a model in 1st differences is appropriate, the issue of cointegration must be considered. If a cointegrating vector exists between Value, FPat, and Pat, an appropriate model must specify the dynamics correctly by including an error correction mechanism. If it is found that no cointegration exists, a model in first differences is appropriate.

Table 4 Panel Cointegration Tests

All	Test Statistic	Robust P-value
Ga	4.899	0.948
Gt	3.262	0.760
Pt	-0.080	0.236
Pa	-0.833	0.938
31&32		
Ga	3.570	0.908
Gt	2.162	0.658
Pt	-4.005	0.366
Pa	-7.198	0.186
33		
Ga	1.735	0.538
Gt	-5.158	0.318
Pt	-6.048	0.130
Pa	-7.784	0.104

Note: The cointegration tests, which allow for a constant in the cointegrating relationship, are z scores that can be compared to the standard normal distribution. Robust p-values are based on bootstrapped critical values and are robust to cross-sectional dependence. The null hypothesis of no cointegration is rejected if z score is below the critical value.

Table 4 provides four tests of panel cointegration based on Westurlund (2007). In every case we fail to reject the null hypothesis of no cointegration (the details on these tests are provided in the Appendix). The conclusion is that a model in 1st differences, without an error correction specification, is adequate for investigating the relationship between Value, FPat, and Pat, henceforth denoted as dValue, dFPat, and dPat, respectively.

A panel Vector Auto Regression (PVAR) is employed to evaluate the response of first differences of US citation weighted patents to changes in foreign citation weighted patents and changes in real value added. This technique is based on work by Love and Zicchino (2006) who developed a panel VAR model to investigate investment behavior and the degree of financial development. The approach has found use in other areas of economics including studies of innovation. A good review is found in Canova and Ciccarelli (2013). To our knowledge this is the first paper to use a PVAR model to investigate knowledge spillovers.

We begin by investigating a full panel of 14 industries. Given the results reported in Table 3 and Table 4 a PVAR in first differences is the correct specification. A major advantage of the PVAR framework over the empirical methodology employed in the literature to date is that each variable in a Panel VAR model is treated as potentially endogenous. The PVAR is ideal for investigating the dynamic relationship between knowledge and knowledge spillovers between these industries in the US and their foreign counterparts. The estimated model is a *pth* order PVAR where p is order of the autoregressive lag. The panel VAR is specified as follows:

$$\begin{aligned} Y_{i,t} &= A_1 Y_{i,t-1} + A_2 Y_{i,t-2} + ... + A_p Y_{i,t-p} + f_i + u_t + e_{i,t} \\ i &\in \{1, 2, ..., N\}, t \in \{1, 2, ..., T_i\} \end{aligned} \tag{1}$$

The panel is defined by $N = 14$ industries (i) and a total of $T = 28$ years (t) for all i in a strongly balanced panel. The vector $Y_{i,t}$ includes $k = 3$ variables: (1) dValue, (2) dFPat, and (3) dPAT. These transformed (first differenced) variables are stationary and are used to identify the relationship between innovations in foreign patenting and US patenting and vice versa. The industry fixed effect, f_i, absorbs cross-industry variation in the mean of each industry series. In a dynamic setting, the commonly employed mean-differencing procedure would create biased coefficients on the lagged dependent variables (see Arellano and Bover, 1995). Following Love and Zicchino (2006), the cross sectional mean is subtracted from each series to remove any time fixed effects before Helmert forward mean-differencing is implemented to remove industry fixed effects. The time fixed effects, u_t, are included to account for the recent drop and partial recovery in patent activity that is evident across industries for both domestic and foreign citation weighted patent activity. The individual equations are stacked and simultaneously estimated using GMM. In this process $L \geq kp$ instruments are constructed from lagged values of the $Y_{i,t.}$

It is common the use various information criteria such as the Akaike or Bayesian criteria to choose a model structure in time series analysis. Analogous methods are available for a panel of time series data. The concern is the selection of the lag, p, in the PVAR and the selection of the q, the lag in the dependent variables used in instrumentation. The criteria used in a PVAR are based on Hansen's J statistic for over identifying restrictions and are, therefore, only available when $q > p$, in an over identified model. These Consistent Model Moment Selection Criteria

(CMMSC) are reported in Table 5. Three CMMSC criteria based on the Bayesian, Akaike, and Hannan-Quinn information criteria are arranged in the table. Using q=5 lags per variable the three CMMSC statistics are calculated for lags 1 through 4.

Looking at the full panel, the MBIC and the MQIC criteria both pick a single lag. The MMSC picks a lag of 3. A model structure with 3 lags leads to 9 Eigen values. This structure leads to the modulus of one Eigen value outside of the unit circle and two Eigen values very close to the unit circle. A single lag leads to three Eigen values, all well within the unit circle.[7] The results reported below are based on a one lag PVAR.

Table 5 Optimal Lag Selection

Lag	MBIC	MMSC	MQIC
All			
1	-145.8767	-11.59313	-65.28591
2	-111.1176	-10.4049	-50.67448
3	-81.57953	-14.43773	-41.28412
4	-38.66526	-5.094357	-18.51755
31&32			
1	-108.9334	-11.71611	-51.14797
2	-84.10921	-11.19624	-40.77014
3	-64.69094	-16.08229	-35.79822
4	-36.06864	-11.76432	-21.62228
33			
1	-92.42331	-13.38746	-45.50568
2	-55.71253	-3.021964	-24.43411
3	-28.2977	-1.952422	-12.65849
4	0	0	0

$MBIC = J - (\,|q| - |p|\,)k^2 \ln(n), MMSC = J - 2(\,|q| - |p|\,)k^2,$
$MSC = J - 2(\,|q| - |p|\,)k^2, MQIC = J - R(\,|q| - |p|\,)k^2 \ln(n).$
In each case J is Hansen's J for over identification.

The estimated coefficients of Equation 1 are reported in Table 6. While it is possible to calculate Granger causality tests, they are not necessary with a single lag. It is clear that changes in US patents are Granger caused by changes in real value added and changes in foreign patenting activity in the US. Likewise changes in foreign patents are Granger caused by changes

[7] The Eigen values of the 1 lag PVAR are .74, .61, and .42.

in real value added and changes in US patenting activity. Changes in domestic patents Granger cause changes in real value added.

Table 6 PVAR Coefficients: All Industries

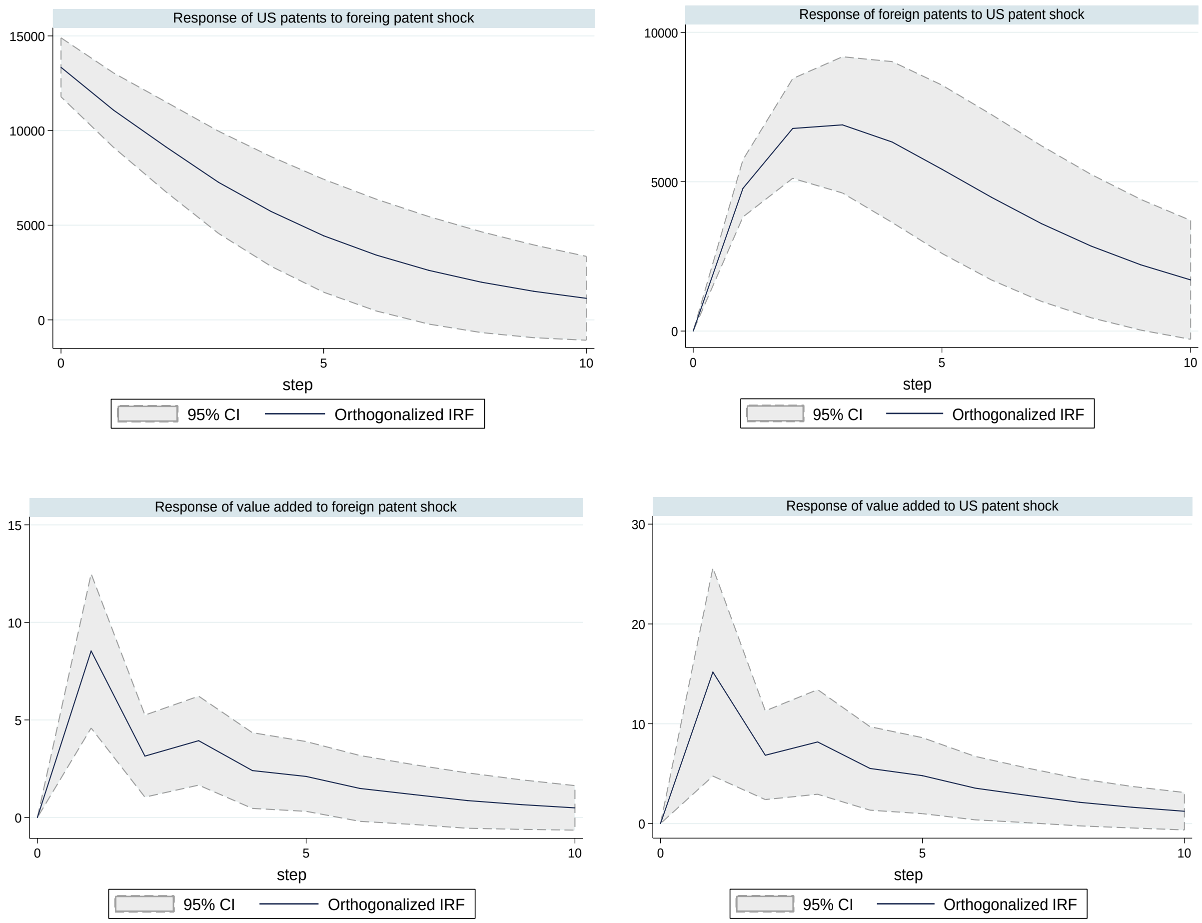
dValue	Coeff	SE	Z	P-value
dValueL1	-.4224984*	.0707694	-5.97	0.000
dPatL1	.0013848*	.0004843	2.86	0.004
dFPatL1	-.0014049	.0008571	-1.64	0.101
dFPat	**Coeff**	**SE**	**Z**	**P-value**
dValueL1	19.34668*	2.926158	6.61	0.000
dPatL1	.4357614*	.0392505	11.10	0.000
dFPatL1	.042496	.0864129	0.49	0.623
dPat	**Coeff**	**SE**	**Z**	**P-value**
dValueL1	17.79214*	6.045447	2.94	0.003
dPatL1	1.315546*	.1153113	11.41	0.000
dFPatL1	-.914959*	.2229234	-4.10	0.000

*indicates significance at 1% level.

It is important to remember that these coefficients are not structural parameters. The estimated coefficients are functions of contemporaneous structural coefficients and cannot be used to evaluate the role of foreign knowledge spillovers on US innovation or value added without further restrictions. The most common means of identifying structural shocks is to employ a Choleski decomposition of the variance-covariance matrix of residuals and investigate impulse response functions.

The Choleski decomposition is a recursive or triangular decomposition requiring an ordering of the variables such that contemporaneous correlation for any pair of variables is assigned to shocks in the variable ordered first. This decomposition exactly identifies the structural parameters. For example, the ordering of: (1) dValue, (2) dFPat, (3) dPat implies that innovations in dValue have a contemporaneous impact on dPat and dFPat and that dFPat has a contemporaneous impact on dPat but not dValue. This ordering is motivated by evidence, outlined in the introduction, that innovative activity follows the business cycle and the idea that innovations are geographically localized and take time to adapt for and spread to foreign markets. Figure 5 presents IRFs from periods 0 to 10.

Figure 5 Impulse Response Functions: All Industries



The top left panel of Figure 5 shows the response of US citation weighted patent activity to a one standard deviation increase in foreign citation weighted patent activity. A one standard deviation change in dFPat is 12,505 patents and this leads to a large contemporaneous increase in US citation weighted patents of 11,177 patents, nearly as large as a change in domestic citation weighted patenting activity. The impacts are statistically significant, as seen from the 95% confidence bands. The impact of a one time innovation to citation weighted foreign patent activity is also long lived, after 5 years the response is 1,022 US citation weighted patents and after 10 years the response is 102 citation weighted patents. The initial response, however, is only 46% of one standard deviation in citation weighted US patents. Though the shock to dFPat has the expected impact on US value added (see the lower left panel) the result is not statistically significant. It would take a large shock to foreign citation weighted patents to generate a significant effect on US industry value added. It is important to remember that the model accounts for the direct influence of foreign innovation on US productivity, an impact that includes indirect channels of technological diffusion and trade in intermediate goods.

The top right panel of Figure 5 shows the response of citation weighted foreign patent activity to a one standard deviation increase in US citation weighted patent activity. A one standard deviation change in dPat is 24,401 patents and this leads to a contemporaneous increase in foreign citation weighted patents of 5,282 foreign patents at the one period lag. This impact is highly significant and, as in the case of foreign citation weighted patents on US citation weighted patents, long lived. Note that the impulse in citation weighted US patents is about twice as large as the impulse in dFPat, but the response in dFPat in the upper right panel is just half the response in dPat in the upper left panel. The lower right panel shows the impact of US citation weighted patent shocks on US real value added. The impact of a one standard deviation increase in US citation weighted patents has a significant impact on value added.

The asymmetric response of foreign citation weighted patents to US citation weighted patents compared to the impact of a one standard deviation increase in foreign citation weighted patents on US citation weighted patents is consistent with the idea that technology is geographically localized and foreign patent activity in the US represents foreign technology that has been made ready for US markets. Clearly an increase in US patents leads to a much lower impact of foreign patent activity in the US, indicating that much of the knowledge these patents represent are geographically idiosyncratic and local to the US economy. However, the positive impact of domestic citation weighted patents on foreign patent activity in the US does indicate that the US has strong absorptive capacity.[8]

The interpretation of the results is evident in the forecast error variance decomposition (FEVD). It is useful to decompose the forecast error variance into the proportions due to each type of shock. The variance decomposition is reported in Table 7, which shows the percentage

[8]It is important to note that direct spillover effects that we find are within industries, as the model does not allow for direct cross-industry knowledge spillovers.

of long-run variation in each variable that is explained by each shock in the estimated VAR. This decomposition for each variable is shown at forecast horizons of 5, 10, and 20 years. It is common to find that a large degree of variation in a variable is due to its own innovations, but a considerable amount of the variation in changes in weighted US patenting (13-16%) is explained by innovations to the change in weighted foreign patents. However, this variation in foreign citation weighted patent activity has a very small impact on US value added, explaining less than .2% of the variation in value added. US citation weighted patent activity explains a more sizable 6.5% of the variation in value added at 10 and 20 year horizons.

A larger percentage of the variation in changes in weighted foreign patents is explained by changes in weighted US patents over various forecast horizons (61-70%). This is also highly indicative of a strong absorptive capacity in the US. While the IRFs and FEVDs clearly support the hypothesis that there are important links between US and foreign innovation that go beyond the indirect channel of spillovers on value added, the role of the direct channel is likely to be limited in economic significance.

Table 7 FEVD

	impulse		
response dValue	dValue	dFPat	dPat
h=5	.9404547	.0016717	.0578736
h=10	.9331383	.0016802	.0651814
h=20	.9326347	.0016795	.0656857
	impulse		
response dFPat	dValue	dFPat	dPat
h=5	.0138117	.3754795	.6107088
h=10	.0160337	.2903017	.6936647
h=20	.0162403	.2842333	.6995265
	impulse		
response dPat..	dValue	dFPat	dPat
h=5	.0183021	.1558226	.8258752
h=10	.0193615	.1290026	.8516359
h=20	.0194584	.1271431	.8533984

In order to further investigate the significance of the direct channel for knowledge spillovers the same methodology is applied to slightly less aggregated panels. Looking at the two specifications for similar 2 -digit industries in Table 5 it is clear that the optimal lag length remains equal to 1. Table 8 presents the PVAR reduced form coefficients.

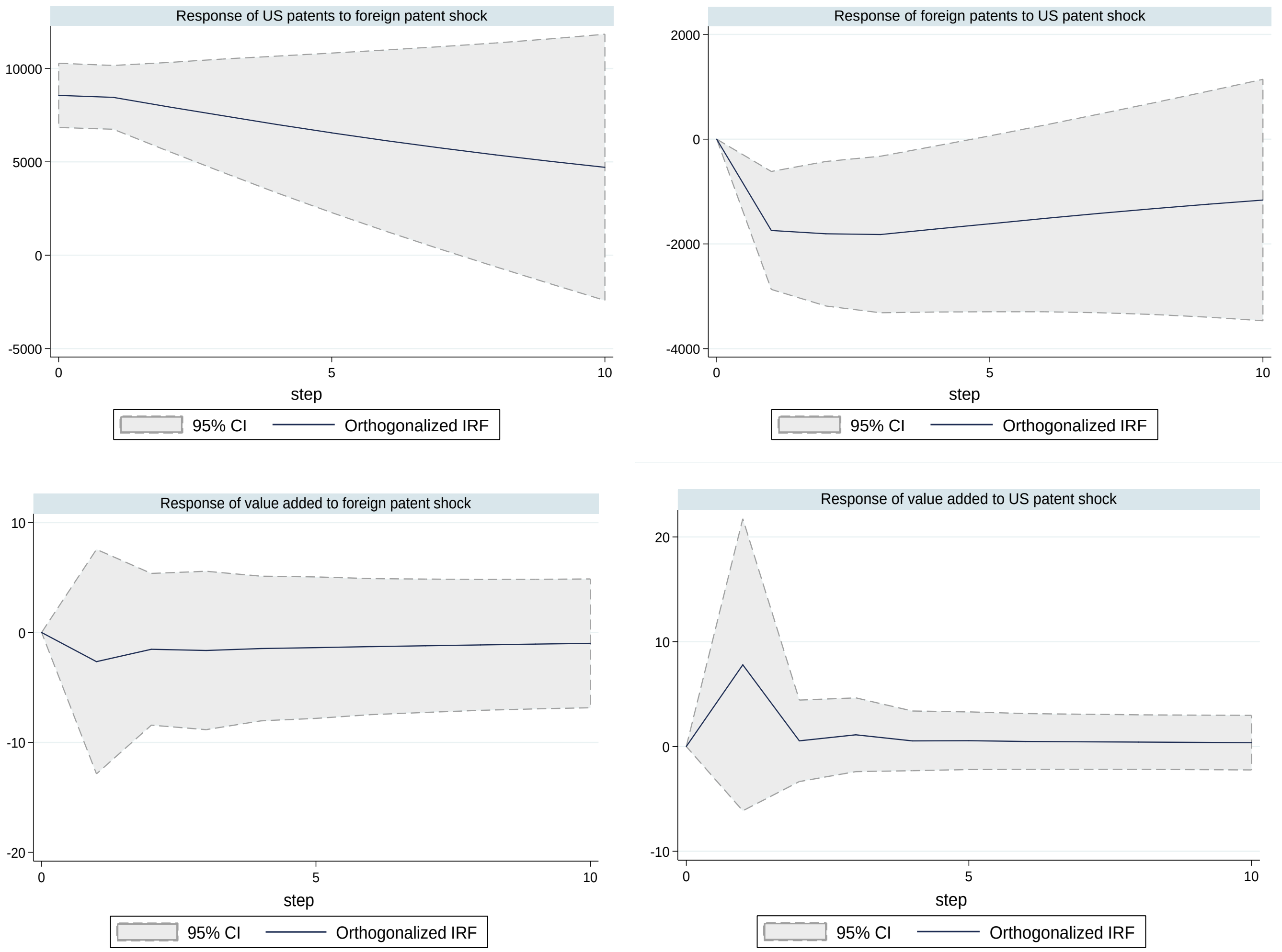
Table 8 PVAR Coefficients: Disaggregated Panels

Two Digit 31&32					Two Digit 33				
dValue	Coeff	SE	Z	P-value	dValue	Coeff	SE	Z	P-value
dValueL1	-.290443*	.0992531	-2.93	0.003	dValueL1	-.5629044	.0674378	-8.35	0.000
dPatL1	-.0022341	.0022486	-0.99	0.320	dPatL1	-.0014052	.0007565	-1.86	0.063
dFPatL1	.0012227	.0010653	1.15	0.251	dFPatL1	.0016134	.0004189	3.85	0.000
dFPat	Coeff	SE	Z	P-value	dFPat	Coeff	SE	Z	P-value
dValueL1	41.61873*	6.072194	6.85	0.000	dValueL1	9.06024*	2.481525	3.65	0.000
dPatL1	1.361777*	.1733257	7.86	0.000	dPatL1	-.141147*	.0463898	-3.04	0.002
dFPatL1	-.273286*	.0912107	-3.00	0.003	dFPatL1	.5320518*	.0162603	32.72	0.000
dPat	Coeff	SE	Z	P-value	dPat	Coeff	SE	Z	P-value
dValueL1	62.17262*	10.29526	6.04	0.000	dValueL1	-19.0837*	6.143473	-3.11	0.002
dPatL1	1.643522*	.3040632	5.41	0.000	dPatL1	-1.51722*	.1650783	-9.19	0.000
dFPatL1	-.1395098	.1641041	-0.85	0.395	dFPatL1	1.633414*	.0873189	18.71	0.000

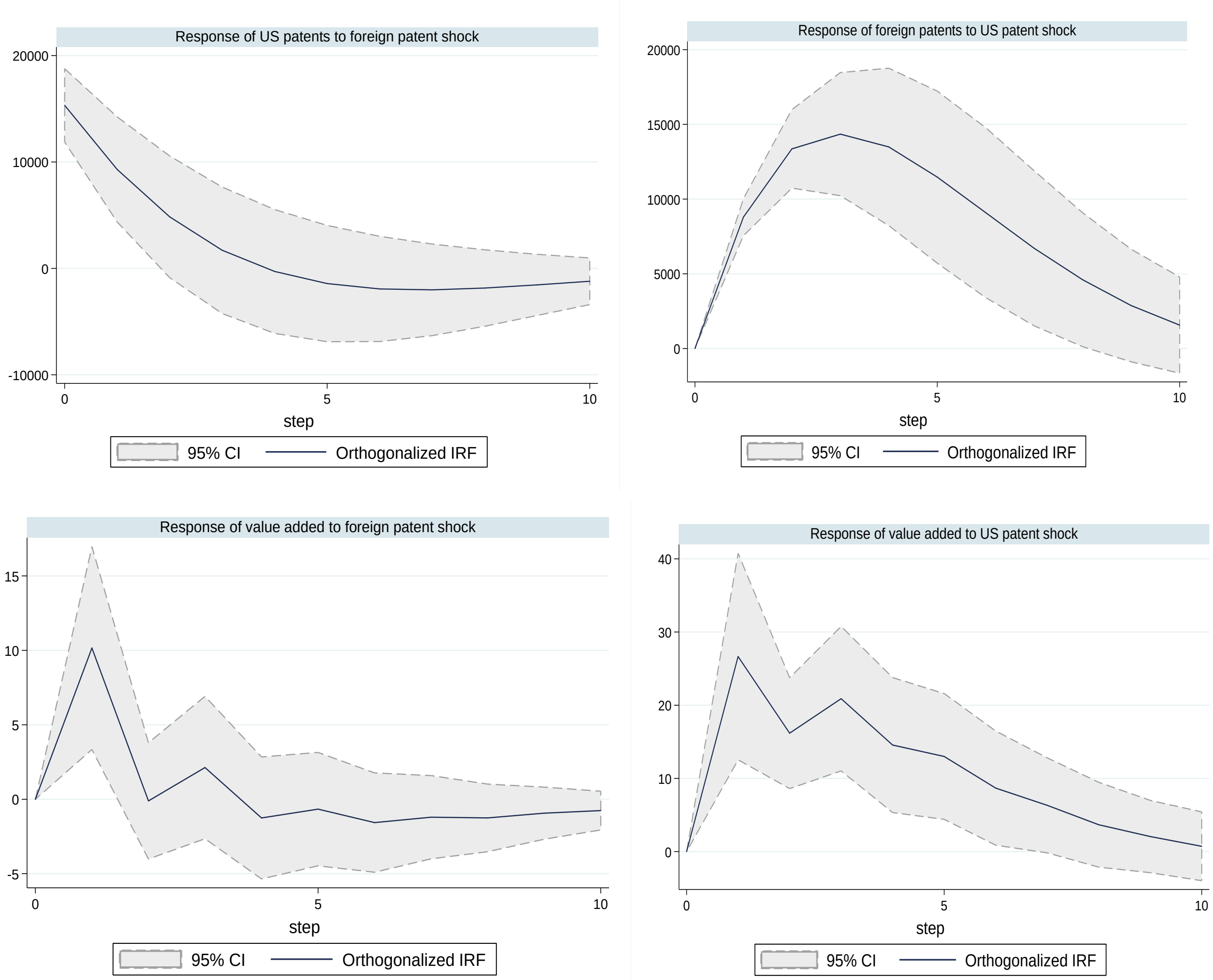
*indicates significance at 1% level.

Figure 6 presents the IRFs for disaggregated industries. The estimation for a panel of 31 and 32 2-digit industries includes industries such as Chemicals, Food, Textiles, Paper Products and Wood Products. These industries show patterns different from the aggregated results reported above. First, though a one standard deviation shock to dFPat has a significant and positive impact on dPat the impact of a one standard deviation change in dPat has a significantly negative impact on the amount of foreign citation weighted patenting in the US, dFPat. Furthermore, neither of these shocks has a significant impact on value added, though the movement in value added in response to a shock in domestic citation weighted patents is in the expected direction.

Figure 6 Impulse Response Functions: Two Digit Industries 31&32



Two Digit Industries 33

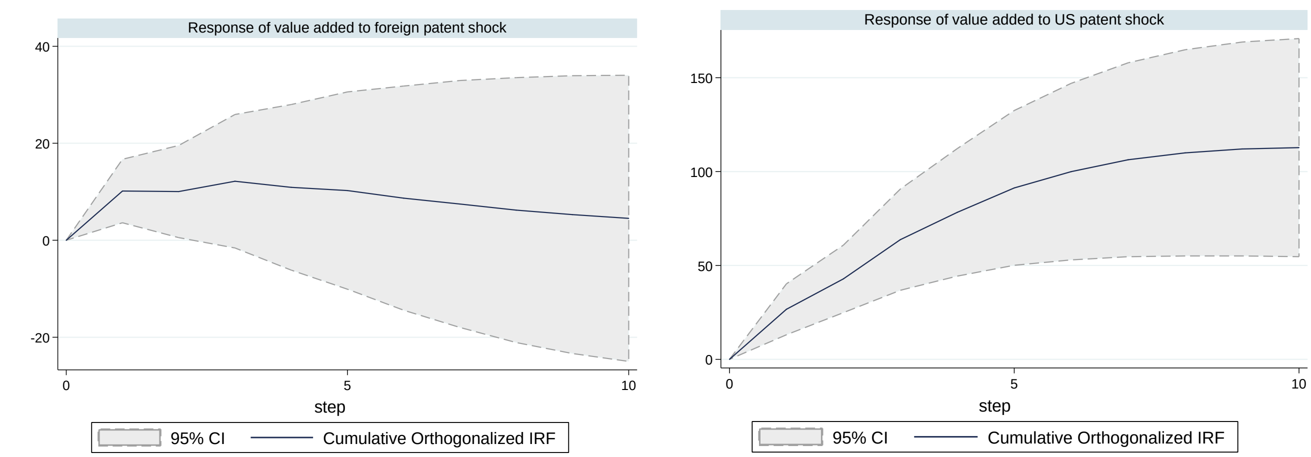


The dynamics of the 2 digit panel of industries in 33 are very different from the dynamics in the industries in the 31 and 32 2-digit industries. The 33 2-digit industries include Computers, Electronics, Machinery, and Fabricated Metals. The dynamics are qualitatively similar to those reported in the all industry panel. Quantitatively, the impact of domestic citation weighted patents is about 2.5 times the impact of foreign citation weighted patents on value added. The most important difference is related to the impact of foreign citation weighted patent activity in the US on value added, it is now statistically significantly positive. This impact, as already mentioned, is still much smaller than the impact of domestic citation weighted patent activity.

In addition the impact of foreign citation weighted patent activity on value added is of much shorter duration than the impact of domestic citation weighted patent activity, about 2 years in response to an impulse from dFPat compared to more than 10 years following an impulse to dPat.

The response of dValue from an impulse in dFPat is positive and significant over a two year horizon, and then turns negative but insignificant before returning to zero. This suggests that, while there is a positive short run increase in dValue following a shock to dFPat, the long run response of dValue to a shock to dFPat is questionable. Figure 7 presents Cumulative IRFs in order to shed some light on this issue.

Figure 7 Cumulative Impulse Response Functions: Two Digit Industries 33



It is clear that a shock to dFPat leads to a significant short run response in dValue after 2-3 years, however, the significance of the cumulative response of dValue to a dFPat shock is insignificantly different from zero. On the other hand, the cumulative response of dValue to a shock to dPat is both large and significant. US 2-digit industries classified as 33 do benefit from foreign citation weighted patent in the US, but the magnitude and duration of the response of value added is a fraction of the response in value added to shocks in domestic citation weighted patent activity.

6 Conclusion

This paper analyzes international knowledge spillovers using a panel VAR methodology. The importance of investigating international technology spillovers stems from the fact that they are seen as important sources of economic growth and productivity/ income convergence. However, the current literature has had difficulty empirically separating direct and indirect knowledge spillovers. A panel VAR methodology allows us to investigate the role of direct knowledge spillovers by looking at citation weighted domestic patents, citation weighted foreign patents and value added for 14 manufacturing industries over the period of 1977-2004. The benefit of the panel VAR is that it enables us to address endogeneity concerns by treating each variable symmetrically in a fully dynamic model. By pooling data across US manufacturing industries and allowing for fixed effects more efficient and complete estimates of dynamic relationships between domestic and foreign innovative activity are possible.

The results indicate that there is a statistically significant direct knowledge spillover channel impacting US innovation, but the direct channel's impact on domestic US value added is limited. Large changes in foreign citation weighted patents are required if a statistically significant impact on US value added is to be expected. Furthermore, the dynamics uncovered in this paper suggest very different roles for direct spillover channels across industries. The benefits of foreign innovation, where they are realized, are of shorter duration and limited in magnitude compared to the role of domestic innovative activity. In addition, very little of the variation in domestic value added can be explained by foreign citation weighted patent activity. The story is quite different when looking at the role of domestic citation weighted patents on domestic value added. In a full panel, foreign citation weighted patent activity in the US also responds significantly to impulses in citation weighted US patent activity suggesting the importance of absorptive capacity. Though many recent theories of trade, growth and convergence emphasize the role of direct knowledge flows, we find strong evidence that these knowledge flows might not be universally economically significant.

The US economy is highly advanced and has excellent absorptive capacity. One might expect the US to be in an excellent position to benefit from direct spillovers of knowledge. While there is strong evidence that US patenting activity does benefit from foreign innovation, the impact on US value added is small relative to the role of innovation originating from within the US. This result certainly deserves further investigation considering the mechanisms tested in this paper are central to modern theories of trade and growth. The US economy is very unique both in terms of its absorptive capacity and its proximity to the global technological frontier. A combination of absorptive capacity and a significant technology gap might be required to realize significant benefits from knowledge spillovers, suggesting that there may be a more prominent role for direct spillovers in some developing economies. Future research should investigate this possibility.

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7 Appendix

7.1 Matching of Various Classifications

Table A1 Matching of USPTO to NAICS and BEA Classifications

USPTO Code	Product Field Title	NAICS Code
1, 2	Food; Beverage & Tobacco Products	311, 312
3	Textiles, Apparel & Leather	313, 314, 315, 316
4	Wood Products	321
5	Paper, Printing & Support Activities	322,323
6	Chemicals	325
11, 25, 26	Plastics & Rubber Products; Other Transp. Equipment	326, 3364, 3365, 3366, 3369
12	Nonmetallic Mineral Products	327
13	Primary Metal	331
14	Fabricated Metal Products	332
15	Machinery	333
16	Computer & Electronic Products	334
22	Electrical Equipment, Appliances, & Components	335
24	Motor Vehicles, Trailers and Parts	3361, 3362, 3363
27, 28	Furniture & Related Products; Miscellaneous Manufact.	337, 339

Note: USPTO to NAICS concordance is obtained from
http://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/naics_conc/2008_diskette/read_me.txt.
NAICS to BEA industry match is conducted based on http://www.bea.gov/industry/gdpbyind_data.htm.

7.2 Tests of Panel Cointegration

Table 4 provides four tests of panel cointegration based on Westurlund (2007). The tests are based on the following specification:

$$dPat_{i,t} = \delta_t' a_t + \alpha_i (Pat_{i,t-1} - \beta_i' x_{i,t-1}) + \sum_{j=1}^{p_i} (\alpha_{i,j} dPat_{i,t-j}) + \sum_{j=1}^{p_i} \left(\gamma_{i,j} dx_{i,t-j}\right) + e_{i,t}, \qquad (2)$$

where d is a first difference operator, $a_t = [1]$, and $x_{i,t} = \begin{bmatrix} Value_{i,t} & FPat_{i,t} \end{bmatrix}'$. This test of panel cointegration requires a balanced panel. The deterministic components, a_t, allow for a stochastic trend. The second term is the error correction mechanism, where α_i is panel i's speed of adjustment parameter. The lag length, $p_{i,}$ for each time series is chosen based on the best AIC. If the levels of Value, FPat and Pat are cointegrated, it is expected that $\alpha_i < 0$. The test for panel cointegration is a test of the null hypothesis that $\alpha_i = 0$ for all i. The first two tests are group means tests for cointegration, in which the appropriate alternative hypothesis is $\alpha_i < 0$ for at least one i. The second two tests restrict the α_i to be equal across panels such that the appropriate alternative is $\alpha_i = \alpha < 0$ for all i. The robust p values reported in Table 4 are bootstrapped and account for the possibility that there is cross sectional interdependence in the error terms, $e_{i,t}$. In every case we fail to reject the null hypothesis of no cointegration.