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Essays on Regional and Firm-Level Productivity, Military Spending, and Technology

A Dissertation submitted in partial satisfaction of the

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in

Economics

by

Bryan Daniel Goudie

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2008

The Dissertation of Bryan Daniel Goudie is approved, and it is acceptable in quality and form for publication on microfilm:

Chair

University of California, San Diego

2008

DEDICATION

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ABSTRACT OF THE DISSERTATION

Essays on Regional and Firm-Level Productivity, Military Spending, and Technology

by

Bryan Daniel Goudie

Doctor of Philosophy in Economics

University of California, San Diego, 2008

Professor Valerie A. Ramey, Chair

The aggregate response of labor productivity to changes in technology and government spending has been analyzed and documented by many economists. However, much less is known about the response of regional and firm-level labor productivity. Therefore, the first chapter of this dissertation examines the regional effect of an aggregate technology shock. The second and third chapters use firm-level and regional data to explore how labor productivity and technology react to changes in government spending through military contracting. These regional and firm-level responses can help to increase our understanding of aggregate economic fluctuations.

Chapter 1 of this dissertation estimates the response of state-level labor productivity to a technology shock as measured by aggregate utility patent applications.

The state-level responses, estimated with a vector autoregression, have considerable spatial variation. In some states, the responses are significantly positive shortly after the shock. However, in other states the productivity responses are initially negative followed by an eventual positive response. To explain why the U.S. states respond differently, the responses are regressed against a variety of state-level demographic, economic, and policy factors. These cross-sectional regression results indicate that high-skilled labor, density, and industrial specialization are important shortly after a technology shock.

Chapter 2, which is co-authored with Lone E. Christiansen, examines whether changes in government spending, through military prime contract awards, leads to the development of new technology and analyzes the effects on firm-level productivity. Though it is most often assumed that government spending does not affect technological progress, the results from this chapter show that indeed firm-level patenting, a proxy for technology, increases in response to a military contract award. Firm-level sales per employed worker, and research and development are also shown to respond positively.

Chapter 3, co-authored with Lone E. Christiansen, follows the approach in Chapter 2 but examines the effects of military prime contracts at the regional level. The analysis shows that at the regional level, military prime contracts lead to the development of new technology. However, labor productivity at the regional level is only affected insignificantly.

Chapter I

Regional Effects of Technology Shocks

Abstract

This chapter estimates the response of state-level labor productivity to a technology shock as measured by aggregate utility patent applications. The state-level responses, estimated with a vector autoregression, have considerable spatial variation. In some cases, such as New York, Arizona, and Illinois, the responses are significantly positive shortly after the shock. However, in other states, such as Kentucky, Oregon, and Tennessee, the productivity responses are initially negative followed by an eventual positive response within ten years. Chapter I also combines state-level demographic, economic, and policy factors, such as population density, education, and income tax, with the cross-section of labor productivity responses to explain the differential state responses to a technology shock. The cross-sectional results indicate that high-skilled labor is important shortly after the shock, while less-skilled workers become important at the longer horizon. Also, the results suggest that regions that are denser and more specialized, as measured by industrial diversity, tend to have a higher short-run productivity response following a technology shock.

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I.A. Introduction

After two decades of relatively low productivity growth, the U.S. economy finally observed a sustained increase in labor productivity growth in the mid-1990s. This happened after large investments were made in the information technology sector. However, there are substantial economic differences across the U.S. regions. Depending on the initial economic conditions in the contiguous states, the labor productivity in these areas may not have responded symmetrically to technology shocks.

This chapter of the dissertation examines the regional effects of an aggregate technology shock in the U.S. The aggregate technology shock is identified through the use of total utility (invention[1]) patent applications in the U.S. This takes into account that states may be affected by technology developed in other regions and not exclusively within the state itself. Chapter I argues for the strengths of using aggregate patent data to measure technological progress instead of state-level patent application data, which do not capture all new patents that are important for any given state. Additionally, this chapter shows that the results are robust to including many different conditioning variables.

This chapter also estimates the state effects using research and development (R&D) as an alternative measure of technological progress. Employing R&D data as the measure of technological progress leads to results that strengthen the findings from the patent analysis. Furthermore, important differences between the R&D and patent results

[1] The United States Patent and Trademark Office (USPTO) naming convention for invention patents is utility patents.

arise corresponding to the lag from when R&D is performed and until technologies are created and patents applications are filed.

The response of productivity to a technology shock is shown to differ at the state level. These differences are examined carefully with a collection of state-level economic, demographic, and policy characteristics. The selection of factors includes the level of education, industrial diversification, and state-level policy factors such as taxes on wages. Carlino and DeFina (1998) mention that a different mix in large versus small firms may be important in explaining differential effects of monetary policy. Similarly, this chapter explores if establishment size is important in explaining the differential effects of technology shocks.

The structure of this chapter of the dissertation is as follows. Section I.B. reviews the relevant existing literature in order to identify the gap in the literature that this chapter fills. Section I.C. presents the data and discusses advantages of using patent data as a measure of technological progress. Section I.D. contains an overview of the methodology used for the empirical estimates, and Section I.E. presents the empirical results from state-level vector autoregressions. The vector autoregressions show how the effects of a technology shock slowly spread across the U.S. Section I.F. analyzes why states are affected differentially by a technology shock and identifies factors that help explain the different short-run effects. Section I.G. concludes.

I.B. Relevant Literature

Many papers in the macroeconomics literature have explored the aggregate effects of technology shocks, using a variety of identification methods. Gali (1999), Francis and

Ramey (2004), and Christiano, Eichenbaum, and Vigfusson (2003) use long-run restrictions in order to identify a shock that is the sole source of permanent effects on productivity. This shock is labeled a technology shock. However, changes in factors such as human capital and nutrition may also lead to permanent effects on productivity. If this is the case, then the identifying assumption used to isolate the technology shock could result in a series that contains movements unrelated to technology. When this series is then used in analysis, it might cause short-run effects of the shock to be misleading and unreliable.

Basu, Fernald, and Kimball (2006) avoid using long-run restrictions by constructing a purified total factor productivity (TFP) series that accounts for varying utilization, non-constant returns to scale, imperfect competition, and aggregation effects. However, their cleaned TFP series may also capture other factors than technology, such as human capital.

An alternative to long-run restrictions and purified TFP is to use a direct measure of technological progress. Alexopoulos (2006), Christiansen (2008), and Shea (1998) all take this approach. Alexopoulos (2006) introduced an index for technology based on the number of new book titles in the field of technology and computer science. Though her novel series is very interesting, it may be capturing the diffusion of technology more than innovation as many new books become published when a given technology becomes widely adopted.

This chapter of the dissertation uses the total number of utility patent applications as the measure of technological progress in order to avoid imposing long-run restrictions or identifying a technology shock based on a cleansed measure of total factor productivity as in Basu, Fernald, and Kimball (2006). This chapter lies the closest to Christiansen (2008) and Shea (1998) in its choice of technology variable as they also use patent statistics as a measure of technological progress. Shea (1998) performs an industry analysis and finds that a positive patent shock leads to an increase in input use in the short run. However, he does not find significantly positive effects on measured total factor productivity. In addition, several problems are associated with distributing patent statistics at the industry level, as there is no clear methodology for distinguishing between the industry that creates the patent and the industry that utilizes the patent.

Christiansen (2008) showed using patent application data from 1889-2002 that a technology shock can result in labor productivity falling below trend temporarily. At the aggregate level she found this to be the case in the pre-WWII era, whereas she did not find evidence of productivity slowdowns during the post-WWII period. Although the aggregate post-1948 effects do not indicate a temporary slowdown in productivity growth as a result of the arrival of new technology, there may be differential effects at the regional level. Depending on the initial economic and structural conditions of a given state, it may experience a temporary slowdown or an initial increase in labor productivity growth in response to a technology shock.

Carlino and DeFina (1998, 1999) find that monetary policy shocks affect U.S. regions differentially. Performing a regional analysis of the effects of technology shocks can give further insights into the aggregate effects found in the literature.

If the arrival of new technology can lead to temporary adverse effects on productivity, it is important to isolate factors that can explain this phenomenon. Indeed some papers have focused on finding explanations for why productivity can fall below trend temporarily as a result of a technology shock. Among these are Greenwood and Yorukoglu (1997) and Hornstein and Krusell (1996). It is argued in these papers that learning and compatibility problems between the existing and the new technologies are among factors that may explain temporary adverse effects.

Regardless of factors that may result in temporary adverse effects on productivity of a technology shock, the microeconomic literature has provided thorough evidence that new technologies are being adopted slowly across time throughout the economy. Papers that have provided evidence thereof include David (1990), Hall (2004), and Rogers (1995). They argue that the adoption and diffusion of technologies is not immediate and that diffusion of technology follows an S-shaped curve with low adoption initially followed by a rapid rate of adoption and then tapering off as the technology is fully integrated into the economy. As explained in Christiansen (2008), there is thereby no reason to expect large positive effects of a technology shock immediately upon arrival of the new technological advances. However, at the regional level there may be states that adopt new technologies more rapidly than others, thereby leading to differential labor productivity responses. Analyzing these regional differences can give additional understanding into the aggregate effects.

At the spatial level of aggregation, several papers in the microeconomic literature have explored the regional patterns of patenting and citations of patents. Varga (1999) refers to the fact that “innovational activities have a predominant tendency to cluster spatially”. Acs, Anselin, and Varga (2002) compare an innovation output indicator, developed by the U.S. Small Business Administration, to patent data from the United States Patent and Trademark Office at the regional level. They find that the two measures of technological progress provide similar results, and their findings thereby support the use of patent counts when examining technological change. Furthermore, Anselin, Varga, and Acs (1997) have examined the local geographic spillovers between university research and high technology innovations. They found a positive relationship between university research and innovative activity.

Varga (2000) found, using U.S. metropolitan areas, that local academic knowledge transfers were positively affected by agglomeration, and that concentration of high technology employment is an important agglomeration factor in promoting knowledge transfers. Further, Varga and Schalk (2004) empirically investigate the role of localized factors of technological change in macroeconomic growth using Hungarian data. They argue that the economic spatial structure is an important factor in macroeconomic growth.

Kouparitsas (2002) explores whether regional business cycles are driven primarily by common or region specific shocks. Kouparitsas finds that spillovers of region-specific shocks across regions account for a relatively small fraction of business cycle variations, but that common shocks account for a large and significant fraction of regional business cycle variations. The fact that common shocks are important supports the approach in this chapter of considering the effects of an aggregate technology shock. Keller (2002) finds in a cross-country study that diffusion is geographically localized such that the effects of R&D on productivity decline with geographic distance. In addition, Jaffe, Trajtenberg, and Henderson (1993) find that knowledge spillovers are geographically localized in the sense that patent citations are more likely to come from the same geographic area as the cited patents. However, geographic localization is found to fade slowly over time, and basic inventions are not found to diffuse more rapidly than other inventions.

Other papers of interest include Audretsch and Feldman (1996), Carlino and Sill (2001), Rauch (1993), and Lin (2007). The first explores spillovers from research and development, while the second examines the importance of common trends and common cycles in regional data. Rauch (1993) finds a strong connection between productivity gains and human capital at the city level. The cross-sectional analysis in Lin (2007) explores the factors that create advantages for regions in attracting new occupations. Interestingly, he finds that regions with highly educated individuals and a broad industrial base are more likely to attract new work.

I.C. Data

Technological progress in this chapter of the dissertation is measured by the number of total annual utility[2] patent applications filed in the U.S. from 1963 to 2005. Christiansen (2008) employs these data in an aggregate analysis. Her paper argues that problems with using patent data as a direct measure for technological progress are not severe. This chapter differs from the analysis in Christiansen (2008) by examining the regional effects of technology shocks, which may differ importantly from the aggregate results.

[2] The USPTO also reports plant and design patents. The former is granted to an inventor who has invented or discovered and asexually reproduced a distinct and new variety of plant, other than a tuber propagated plant or a plant found in an uncultivated state. The latter consists of the visual ornamental characteristics embodied in, or applied to, an article of manufacture. It is a matter of appearance, as in the shape of a classic Coca-Cola bottle. In 2005, 417,508 patents were applied for and 93% of them were utility (or invention) patent applications.

One potential drawback of the analysis may arise if patent data are only a noisy measure of technological progress as a result of patent law changes across time which may have affected the incentive to apply for a patent. Particularly, there was a surge in the number of U.S. patent applications in the mid-1980s. This surge was analyzed by Kortum and Lerner (1998). They found that the surge in patenting was not specific to the U.S. but that it was also seen in the U.S. patenting numbers abroad. The surge in international patent statistics leads them to conclude that the jump in U.S. patenting is related to a burst of innovation. These findings support the assumption in this chapter that the important source of fluctuation in the patent application series relates to the arrival of new technology and not to institutional changes.[3]

The total number of patent applications sorted by the state of the primary patent author is also available from the United States Patent and Trademark Office (USPTO). However, important new technologies are assumed to affect all regions and not only the state that the patent author cites. Using the state-level patent series would thereby leave out information important for the state-level analysis. Thus, the aggregate patent series is preferred for the identification of technology shocks.

Although all patents are not of equal importance, a new invention with wide applicability and importance such as a general purpose technology (GPT) should lead to a surge in patent applications as many new inventions will occur in response to the new GPT. As fluctuations in the patent series indicate economically important technological change, the patent shock, which will be identified in this chapter, is important not only

[3] To check the robustness of the patent results this chapter also employed data on R&D as an alternative measure of technological progress.

for the industry or region of technological origin but also for industries and geographical areas that employ the new technology as an input to production. For example, the financial industry in New York may be importantly affected by innovations in information technology developed elsewhere. As such, it is important not to rely on patent statistics that are sorted by industry or region but to allow for the full country-wide effect.[4]

At the aggregate level, an alternative to using total patent applications filed in the U.S. is to use the number of patents granted, sorted by application year. Using these data would exclude patent applications that are never granted as a result of not fulfilling the requirement of being useful, novel, and non-obvious. However, data on patents granted, sorted by application year suffers from truncation problems as there is a lag from the date of application till the date of grant. Patents that are applied for in 2005 but not granted until 2008 or later will therefore not be included in the dataset. Figure I-1 plots the natural logarithm of total patent applications together with the natural logarithm of patents granted, sorted by application year and sorted by grant year. The series on patents granted, sorted by application year, is only reliably reported starting in 1966, and as a result of the truncation problem in the end of the sample cannot reliably be used after 1999. The figure clearly shows the fall in the number of patents granted, sorted by application year, which illustrates the truncation problem. As the analysis is based on

[4] This chapter did try to estimate productivity effects of an aggregate patent shock, controlling in the vector autoregression for the number of state-level patent applications. However, state-level patent applications are available only from 1969 to 1996. Using this series therefore severely limits the time series dimension of the analysis, leading to less precise parameter estimates. Additionally, impulse response functions after including state-level patents, although more jagged than the benchmark results for the full sample, follow the same overall pattern as the benchmark results. This indicates that controlling for state-level patent applications in the analysis is not important.

annual data, excluding nine years of data may influence the precision of the estimates. Therefore, the data on total patent applications are used for the benchmark analysis.

Concerns with using total utility patent applications instead of patents granted sorted by application year should not be severe as the two series are very much positively correlated. Indeed, the correlation coefficient between the annual growth rates of the two series from 1967 to 1999 is 0.7. As such, the two patent series follow the same pattern. Furthermore, as a robustness check the impulse response functions were also computed based on the shorter sample of patents granted, sorted by application year. Although more results tend to be insignificant as a result of the reduction in degrees of freedom, the estimates of the impulse response functions did not lead to different conclusions.

Christiansen (2008) and Hall, Jaffe, and Trajtenberg (2001) note that data on patents granted, sorted by grant date, which are also illustrated in Figure I-1, are affected by a varying application-grant lag. Budgetary and staffing concerns at the USPTO, which are unrelated to technological progress, can result in such effects on the application-grant lag. Data on patents granted by grant date are therefore not used as a measure of technological progress.[5]

One potential caveat that this chapter faces is that different patents may be important for different industries. A surge in patenting therefore can affect the states differentially, depending on the industry mix in any given state. To alleviate this issue, this chapter will introduce a variable that captures the industry mix at the state level.

[5] For more information regarding patent statistics as economic indicators refer to Griliches (1990). Also, refer to Hall, Jaffe, and Trajtenberg (2001) for information regarding the NBER patent data file.

Data on gross domestic product by state (GDPS) is collected from the Bureau of Economic Analysis (BEA) and is converted from nominal to real terms using the GDP deflator. Aman, Downey, and Panek (2005) introduced new methodology for estimating the regional product. As a result, a jump in the regional product was introduced starting in 1997.[6] In the analysis below, the data are spliced in 1997 in order to take this change into account.[7] Non-farm employment by state is from the Bureau of Labor Statistics (BLS) Current Employment Survey. Labor productivity by state is then computed as real GDPS per employed worker. The natural logarithm is taken of these variables. In Section I.F., this chapter explores the regional variation in the response of labor productivity to an aggregate technology shock. The data from that cross-sectional analysis will be presented in Section I.F. However, a detailed account of all data is presented in this chapter's Appendix which is contained within Section I.I.

Table I-1 contains information on the extent to which different states contribute to the U.S. economy. Alaska, the District of Columbia, and Hawaii have been left out of the analysis as their economic and demographic characteristics often differ substantially when compared to the 48 contiguous regions.[8] The table shows that average annual labor productivity growth varies considerably from state to state. Montana and North Dakota have the lowest average productivity growth while Connecticut has the highest.

[6] Under the Standard Industrial Classification system (1963-1997), regional product does not include the statistical discrepancy. However, the North American Industry Classification (1997-2005) does incorporate the discrepancy to align regional product more closely with gross domestic product.
[7] This chapter also tried estimating the impulse response functions without splicing the data, instead including a dummy variable starting in 1997. Results from this procedure were very similar to the ones reported in this chapter and it did not change the overall conclusions.
[8] Also, the distance between the satellite states and the mainland is rather large which could unduly influence their response to an aggregate technology shock. Furthermore, an earlier version of this chapter included them in the analysis and it showed that the major conclusions of this chapter were robust to adding the outliers.

Additionally, the correlation between growth rates of state and U.S. aggregate productivity series differ substantially from state to state. Table I-1 also shows that the size of each state economy differs considerably. In 2000, California, New York, and Texas constitute nearly 29 percent of total gross domestic product, while Wyoming, Montana, and North Dakota account for no more than 0.6 percent.

Figure I-2 plots aggregate U.S. labor productivity together with the average state labor productivity and its standard error bands. The U.S. aggregate productivity series lies above the state average, indicating that the states that are most important for the aggregate series tend to have slightly higher productivity. However, the aggregate productivity series lies well inside the standard error bands of the state average. Importantly, as labor productivity growth differs between states it is also likely that state productivity responds differentially to technology shocks, depending on the region. The contribution of this chapter is therefore very important in understanding these differences.

Table I-2 examines the stationarity underlying the data. Both Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are performed. Generally, if the data display properties close to a unit root, while still stationary, it is often hard to reject the assumption of a unit root. Table I-2 shows that for many states both the KPSS null hypothesis and the ADF null hypothesis are difficult to reject. Since stationarity is assumed under the KPSS null and a unit root under the ADF null, it is often difficult to determine the order of integration for the productivity series.[9] In order not to over-difference, this chapter decides to treat the data as stationary around a deterministic

[9] The length of sample, frequency of the data, and overall power of the unit root tests under consideration may be contributing to the consistency by which these tests fail-to-reject the null.

trend. However, time series estimations have also been performed in differences, assuming a unit root. Although this lead to more persistent response functions, the overall results were similar to the ones from the trend stationary statistical model.

I.D. Methodology

First, vector autoregressions (VARs) for each state are estimated, and orthogonalized impulse response functions are computed in order to estimate the response of state productivity to an aggregate technology shock. The reduced-form VAR can be expressed as follows:

$$(1) \qquad Y_{it} = \alpha_{i0} + \alpha_{i1} t + \Phi_{i1} Y_{it-1} + \Phi_{i2} Y_{it-2} + \cdots + \Phi_{ip} Y_{it-p} + \varepsilon_{it} \ .$$

Here, Y_{it} is a vector of variables associated with state i at time t, and α_{i0} is a constant term. α_{i1} is the coefficient on a deterministic time trend, and Φ_{ij} for $j = 1, \ldots, p$ are matrices of coefficients on lags of the endogenous variables. ε_{it} is a vector of errors.

The patent variable (PAT) is ordered first in the recursive ordering, while regional productivity is ordered second. This allows the patent shock to affect productivity contemporaneously. Orthogonalized impulse response functions are then estimated based on a short-run Cholesky decomposition. As a robustness check this chapter also tried the reverse ordering to obtain identification of the shock. Ordering PAT last among the variables does not allow for a contemporaneous response of productivity to a patent shock, and changing the ordering did not affect the overall shape of the impulse response functions. Therefore, these results are not reported below.

The standard errors of the response functions were constructed using standard Monte Carlo simulation methods presented in Hamilton (1994). For each set of standard errors, this chapter used 2000 draws from a multivariate normal.

Following estimation of the vector autoregressions and corresponding response functions, the state impulse responses are collected. Subsequently, this chapter follows the methodology of Carlino and DeFina (1998) who examined the differential regional effects of monetary policy. For this present analysis, Chapter I regresses the impulse response functions at a given horizon on a set of state economic factors. The following cross-sectional equation is estimated:

(2) $$LPF_{ih} = \beta W_i + u_{ih}.$$

LPF_{ih} indicates the impulse response function of productivity to a patent shock at horizon h in state i. W_i is a vector of economic indicators in state i together with a constant term, while u_{ih} is an error term. β is a vector containing the coefficients of interest.

I.E. Empirical Evidence

This section contains the results from estimating the benchmark equation (1), followed by robustness checks of the results.

I.E.1 Benchmark Results

The impulse response functions of productivity to a patent shock for the 48 states are depicted in Figure I-3. The parameter estimates are based on patents and productivity in their log levels, a constant and a time trend. Data for the period 1963 to 2005 are used, and p = 3 lags are included. The Akaike Information Criterion for some states indicated that the number of lags be less than three, however, the overall shape of the response functions are robust to the choice of the lag length. As cross-state comparisons are important to this chapter of the dissertation, three lags were chosen for all regions.[10] The impulse response functions are depicted together with 90% confidence intervals.

Figure I-3 shows how state-level labor productivity differs in its responses to the aggregate technology shock. The vertical axis is in percent and the horizontal axis delineates the time periods following the technology shock. To avoid confusion it should be noted that time period 1 is the period in which the technology shock occurs. That is, the recursive identification used to isolate the orthogonal technology shock together with having patents ordered first allows productivity to respond contemporaneously.

States such as Arizona, Delaware, Illinois, Nevada, Rhode Island, New York, North Carolina, Pennsylvania, and Washington show a significant increase in productivity after a technology shock with no significantly negative short-run effect. Other areas (for example Arkansas, Indiana, Iowa, Kentucky, Mississippi, Nebraska, New Mexico, Oregon, and Tennessee) depict an initial decline in labor productivity as a result of the shock, followed by a later increase. In addition, some states that quickly respond positively to shocks revert to trend faster than several states in the second group which have postponed positive responses.

For comparison, Figure I-4 displays the response of U.S. aggregate productivity to a patent shock. At the aggregate, no significantly negative response is found for this period. Instead, labor productivity slowly increases above its trend level. Figure I-4 also

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[10] If the true lag length is less than three, then given a large enough sample size the estimates of the higher order lags would be near zero. Indeed precision of the estimates is sacrificed for uniformity across the regional VARs.

displays the response of patents to a patent shock using the national labor productivity data as the second variable in the VAR. That response is significantly positive and persistent, indicating that an orthogonal patent shock has a long-lasting effect on patents. These aggregate results are broadly consistent with the post-WWII evidence found in Christiansen (2008). The response of patents to a patent shock for each state-level model is not shown since the responses are similar to the national response shown in Figure I-4.

The state results in this chapter compare to the aggregate findings in Christiansen (2008) who found that the productivity response in the pre-WWII period was characterized by a temporary negative effect while the post-WWII era was distinguished by a delayed positive effect. It is of great interest for the understanding of macroeconomic fluctuations in the post-WWII period to find that even during the post-WWII period, where the aggregate result depicts a slow increase to a higher productivity level, the regional effects differ greatly.

The impulse response functions in Figure I-3 are all plotted based on a VAR with three lags. Under this specification, not all states show significant response functions. However, Figure I-5 shows that if the lag length is varied between two and five lags, then the vast majority of states experience a significant response at some point during the forecast horizon. Since the shapes of the productivity responses are robust to changes in the lag length, it can be concluded that the insignificance of the three lag specification for some states is not critical for the results.

Figure I-6 shows how states within a given region tend to respond similarly to a technology shock. These impulse response functions correspond to the ones shown in Figure I-3 (without standard errors), however they are now sorted by the eight BEA regions[11]. For clarification, Panel A of Figure I-6 plots the BEA regions with their corresponding states. Panels B through I of Figure I-6 subsequently plot the response functions associated with each region. States in New England tend to be positively affected by a technology shock in the short run, after which the responses slowly die out as a result of the trend stationarity in the data. Similar results are found in the Mideast. However, states in the Southeast, the Great Lakes, the Plains, the Southwest, and in the Rocky Mountains tend to have the positive responses a few periods postponed, and most of these have a tendency of showing a temporary negative response shortly after the shock.

With the exception of Oregon, the Far West states experience a positive response of productivity to a technology shock. The response of California is positive but insignificant. However, Section I.E.2.3 explores aggregate R&D expenditure as a proxy for the foundations of new technology. That analysis shows California has a significantly positive response following an R&D shock.

Figure I-7 shows 10 thematic maps, one for each forecast horizon, of the contiguous states. The regions are shaded with one of two colors based on the sign of the impulse response functions. Dark grey indicates a productivity response that is negative and white symbolizes those regions that have a positive response. It clearly can be seen how the positive effects on productivity of a technology shock slowly spread across the U.S. states, starting from the coasts and moving inland. By period 7 all regions have experienced positive returns to the patent shock with the coastal states realizing those

[11] The eight regions are: New England, the Mideast, the Southeast, the Great Lakes, the Plains, the Southwest, the Rocky Mountains, and the Far West.

returns earlier in the forecast horizon. At the end of the forecast horizon, the response functions for Connecticut and New Jersey move from positive to negative, however, the late arriving negative response is highly insignificant for both regions. Furthermore, the results from Section I.E.2.3 will show that both states respond positively to an R&D shock for the entire forecast horizon.

I.E.2 Robustness of the Impulse Response Functions

I.E.2.1 Adding Exogenous Variables

The impulse response functions in Figures I-3, I-4, and I-6 are based on vector autoregressions with a deterministic trend. However, U.S. aggregate productivity may have a break-in-trend in 1973. Greenwood and Yorukoglu (1997) suggest that it is related to technology, however, it may also be the outcome of an oil shock, a change in environmental regulation, or other factors. This chapter therefore also tried including a break in trend in 1973. This resulted in impulse response functions that are very similar to the ones already depicted, and they are therefore not reported.[12]

Davis, Loungani, and Mahidhara (1997) have argued that energy prices have a substantial influence on regional economic activity. Therefore, this chapter tried conditioning on the natural logarithm of a fuel producer price index relative to the overall producer price index (FuelPPI). The benchmark model is therefore adjusted to include the contemporaneous instance and one lag of the FuelPPI series.

$$Y_{it} = \alpha_{i0} + \alpha_{i1} t + \Phi_{i1} Y_{it-1} + \cdots + \Phi_{ip} Y_{it-p} + B_{i1} FuelPPI_t + B_{i2} FuelPPI_{t-1} + \varepsilon_{it} \quad (3)$$

[12] Crone and Clayton-Matthews (2005) and Owyang et al. (2005) both examine the timing of region specific business cycles. An analysis of region specific breaks in trend is left for future work.

Adding FuelPPI is not important for most states, and the results are therefore mainly robust to this change. However, results from a few states are affected by including this energy indicator. In particular, the responses of energy producing states such as Texas, Oklahoma, Wyoming, and Louisiana are importantly affected. Adding FuelPPI for these states leads to responses of productivity to a technology shock that are more positive than when FuelPPI is not included. A graphical comparison of the impulse response functions with and without including the energy indicator is contained in Figure I-11 of this chapter's Appendix. Robustness of the cross-sectional results will be analyzed in Section I.F.2.

I.E.2.2 Truncated Time Series Sample

As the methodology for computing GDPS changed in 1997, ending the sample period before this change can alleviate the problem that the change in data definition may be important in explaining the results. The productivity response functions are therefore recalculated based on data from 1963-1997 and are shown in Figure I-12 of the Appendix. The responses are similar to the results computed based on the full data set, although Connecticut tends to have a more positive response in the short run. A few states also tend to show less positive long-run response functions with the shorter sample period.

I.E.2.3 Research and Development

As an alternative to patent data, research and development (R&D) is another potentially important factor that needs to be analyzed when examining the regional productivity response to a technology shock. R&D precedes any patents that may be developed. Therefore, this section employs real R&D data as an alternative direct measure of technological progress. That is, Chapter I estimates the response of labor productivity to an R&D shock in bivariate state-level vector autoregressions, where R&D is ordered first and productivity second. As was the case in the patent analysis, a time trend is included in the regressions together with three lags of the endogenous variables.

The R&D expenditure data are produced by the BEA in conjunction with the National Science Foundation (NSF). They include private and public expenditures performed in the U.S. and are available from 1959 to 2004. Okubo et al. (2006) and Robbins and Moylan (2007) discuss the estimation procedure and the deflation methodology in constructing the real R&D expenditure series.

The individual productivity responses from the R&D analysis are depicted in Figure I-8. These responses show that some states[13] experience a short-run response which becomes insignificantly negative, followed by a significantly positive response at the longer run. Other states, like California, Illinois, Maryland, Massachusetts, New Jersey, New York, Pennsylvania, Rhode Island, and Virginia exhibit positive responses without initial negative effects. That California's productivity response to patents is insignificant while its response to R&D becomes significantly positive suggests that California may respond to technology with a different timing than the other states. For instance, if much of the U.S. R&D is performed in California, then California may lead the rest of the country in incorporating the aggregate technology shock into its labor productivity.

[13] For example Arkansas, Florida, Idaho, Mississippi, and Nebraska.

Table I-3 reports the leads and lags of the correlations between the growth rates of R&D and patents. This correlation analysis suggests that movements in R&D and patents are positively correlated with a lag of about 2-4 years, as the correlation between R&D growth at time t and patent growth at time t+3 is 0.409. That is, a positive movement in R&D (above the mean R&D growth rate) is likely to be followed by a positive movement in patents (above the mean patent growth rate) in about three years. This lag is intuitive as it may take firms more than one year to convert new R&D into a patentable innovation.

The overall results from the R&D analysis do show some differences when compared to the patent study. Figure I-13 in the Appendix plots the productivity responses from the benchmark model together with those generated using the R&D data.[14] As there is a lag between the two series, it is expected that initial short-run responses may differ from one another. Interestingly, the responses of productivity to a patent shock tend to lead the responses from an R&D shock such that the responses from the patent shock start increasing from their low point sooner than those from the R&D shock. That is, the future positive effects of an R&D shock often show up in the productivity response functions with a longer lag than the positive effects arising from a patent shock. This exactly corresponds to the fact that R&D spending precedes any future patents, and provides additional confidence in the patent data.

Since R&D leads to new technology with a lag and much of R&D is capitalized knowledge of failed research, the patent series continues to be the preferred measure of

[14] It should be noted that the sample period for the two series is not fully comparable as the R&D response functions are based on data ending in 2004, while the patent data end in 2005.

technology. That is, there is a substantial amount of research expenditure that does not produce tangible results. On the contrary, the patent series is the outcome of important R&D that has future potential value. As such, it is preferred to use the patent series as a measure of technological progress.

I.E.2.4 State Wages and Salaries as a Proxy for Productivity

If workers are being paid their marginal product, then the real wage may suffice as a proxy for labor productivity. As a robustness check, this chapter estimates the effect of a technology shock, through utility patent applications, on state-level wage and salary disbursements provided by the BEA regional program. The wage data are, however, first deflated by the BLS Consumer Price Index. This deflation transforms the wage series into real wages.

The wage responses are constructed from a three lag bivariate VAR with patents ordered first and wages second. For a select group of states[15], Figure I-14 of the Appendix plots the productivity and wage responses to a patent shock. These responses show that both productivity and the real wages respond similarly when faced with a patent shock, though the real wage response in some cases is slightly delayed relative to productivity. The lag may indeed be related to the estimation of wages by disbursement rather than by an accrual method. Nevertheless, for most states the wage and productivity response functions are very similar.[16] As such, these results suggest that changing the metric for productivity will not have a substantial influence on the results. As workers

[15] One state from each BEA area: Massachusetts, New York, Oregon, Tennessee, Utah, Texas, Illinois, and Iowa.

[16] There are a few states including Arizona, Florida, and Washington that have response functions which are different from the benchmark model, however, the impulse response functions for all these states are insignificant.

may not be paid exactly their marginal product, this chapter continues to use the productivity series that is calculated using real GDP and employment.

I.E.2.5 Trivariate Analysis

The bivariate regression results of Figure I-3 control for lag patents and lag productivity. However, other variables, such as labor productivity of the surrounding regions, may influence the relationship between aggregate patents and state-level labor productivity. Therefore, this chapter tried including other potentially important endogenous variables in the state-level VARs. These additional variables are included one at a time together with patents and productivity. A trivariate VAR is thereby estimated. The additional variable is ordered last in the VAR and the equation is estimated using three lags so that the trivariate productivity impulse response functions can be compared to the benchmark results of Section I.E.1. X_{it} in equation (4) indexes the third conditioning variable.

$$(4) \qquad \begin{bmatrix} AggPAT_t \\ LP_{it} \\ X_{it} \end{bmatrix} = Y_{it} = \alpha_{i0} + \alpha_{i1}t + \Phi_{i1}Y_{it-1} + \cdots + \Phi_{ip}Y_{it-p} + \varepsilon_{it}$$

I.E.2.5.1 Surrounding Productivity

The collection of benchmark response functions in Figure I-6 suggests that regions that are close together respond to technology shocks similarly. One explanation for this is that there are region specific shocks that the benchmark model is not accounting for when estimating the effect of an aggregate technology shock on regional labor productivity. Therefore, this chapter tried including the labor productivity of the surrounding regions as the third variable in the state-level VARs. As an example, the third variable in New York's VAR would include the average productivity of the other states in the Mideast[17] BEA region. The surrounding productivity data are constructed using the same methodology as used in the benchmark analysis. That is, the productivity numerator is surrounding GDP deflated using the GDP deflator and the denominator is employment. The natural logarithm is applied to the series.

Figure I-15 in the Appendix contains a comparison of productivity responses from the benchmark and the trivariate VARs where surrounding productivity is the third variable. This selection[18] of plots show that including the spatially relevant productivity data in the state-level trivariate VAR has little to no effect on the productivity response functions from a patent shock. The other state-level responses are not shown as this result holds generally. That the productivity responses are robust indicates that region specific productivity factors are not driving the results. Section I.F. of this chapter takes a closer look at economic policy and demographic factors that may help explain the differences in response functions across the 48 states.

I.E.2.5.2 Manufacturing Employment

The share of manufacturing in employment has declined over the last four decades. Controlling for the manufacturing share in the time series analysis may therefore be of potential importance in explaining the differential state response functions. This section therefore includes the share of manufacturing in employment as the third variable in the VAR. This third variable is only available for the period 1969-2005 and the

[17] Pennsylvania, Maryland, New Jersey, and Delaware.
[18] One state from each BEA area: Massachusetts, New York, Oregon, Tennessee, Utah, Texas, Illinois, and Iowa.

response functions are therefore not directly comparable to the benchmark results. However, the responses of productivity to a patent shock when controlling for the manufacturing employment share are very similar to the benchmark response functions and a small selection[19] of the impulse responses for this analysis are therefore deferred to Figure I-16 of this chapter's Appendix.

As an alternative to controlling for the manufacturing share of employment, this chapter also tried including total non-farm state employment as the third variable. Total employment is available at the state level for the full sample period 1963-2005, and including this variable together with patents and productivity in the VAR did not change the results. These response functions are therefore not reported.

I.E.2.5.3 Real GDP by State

The size of each states economy is another variable that potentially could explain the productivity differences between the 48 states. Figure I-17 in the Appendix therefore reports eight[20] state impulse response functions from a trivariate VAR with patents, productivity, and real GDP. These response functions are compared to the benchmark bivariate responses. As was the case with employment, the time series results are robust to including real GDP by state in the trivariate VAR.

I.E.2.5.4 Density

Controlling for changes in population may be important as the population of some states has increased greatly during the last several decades. In particular, the south west

[19] One state from each BEA area: Massachusetts, New York, Oregon, Tennessee, Utah, Texas, Illinois, and Iowa.
[20] One state from each BEA area: Massachusetts, New York, Oregon, Tennessee, Utah, Texas, Illinois, and Iowa.

states such as California, Nevada, and Texas have experienced a dramatic change in their populations during the last 43 years. This change in population has resulted in corresponding effects on population density.

In order to account for the changes in population, this subsection includes density as a third variable in the VAR. Here, density is defined as number of people per square kilometer in any given state. For a selected group[21] of states, a graphical comparison of the response functions between the benchmark model and the trivariate VAR with density as the third variable is displayed in Figure I-18 in the Appendix. Including density in the time series analysis results in impulse response functions of productivity that are very similar to the benchmark results. Only very few states[22] have impulse response functions that differ from the benchmark after including density in the system. However, the cross-sectional analysis in Section I.F. was also performed using these new impulse response functions, and the main results are robust to this change as will be explained later.

I.F. Explaining Differential State Response Functions

The 48 contiguous states differ substantially in their economic and demographic characteristics. These differences may be important for explaining why regional productivity does not respond uniformly to a technology shock. Table I-4 summarizes sixteen different state-level economic, demographic and policy factors likely to affect the adoption and success of a given technology. In addition, Figure I-9 contains thematic maps and histograms that show how the U.S. states differ in their level of education,

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[21] One state from each BEA area: Massachusetts, New York, Oregon, Tennessee, Utah, Texas, Illinois, and Iowa.

[22] Utah and Colorado are examples of a states whose response functions are somewhat affected by the inclusion of density in the VAR.

industrial diversity, and average marginal tax rates on wages. Together, Table I-4 and Panels A through D of Figure I-9 show that this chapter's state-level economic and demographic factors, such as the share of college educated persons over the age of 25 in the year 2000, exhibit a great deal of spatial variability across the U.S.

In order to examine why a technology shock leads to differential regional effects, Chapter I compares the responses of the 48 states at different forecast horizons to information on the level of schooling, the state industry mix, state policy variables and other relevant factors similar to those used in Owyang et al. (2006) and Carlino and DeFina (1998). Indeed, the arrival of a new technology may affect a region positively shortly after the shock if the area is well equipped to restructure and introduce the new technology in the production function. On the contrary, the same shock may have temporary adverse effects in a state with relatively small amounts of skilled labor which is necessary to quickly incorporate the new technology efficiently.

Jovanovic and Rob (1989) suggest that a high level of human capital will lead to rapid diffusion and growth of knowledge. Bartel and Lichtenberg (1987) and Nelson and Phelps (1966) both suggest that educated workers have a comparative advantage in implementing new technologies because educated individuals can more quickly assimilate new ideas. In order to understand the effects of education on productivity, this chapter considers several different education levels. One variable, EDUhs, captures the share of state population (over the age of 25) with at least a high school education but not a college degree (Panel A of Figure I-9). Another variable, EDUcoll, captures the share of state population (over the age of 25) with a college degree (Panel B of Figure I-9), and

EDUalhs contains the share of state population (over the age of 25) with at least a high school degree. Thereby, EDUalhs is the combination of EDUhs and EDUcoll.

At the short-run forecast horizon, one would expect that a population with a high ratio of college graduates will experience positive productivity responses to the arrival of new technology. On the contrary, states with few college graduates are likely to have short-run adverse effects as learning and implementation of technologies may be more costly. If this intuition is correct, then education should have a positive effect on the response of productivity at the short-run forecast horizon. However, this correlation may be reversed at longer forecast horizons. It is likely that states that quickly see positive productivity effects revert to trend as a result of the stationarity of the data faster than states with delayed positive responses. If states with low-skilled workers have positive effects on productivity eight years after the shock and the productivity of states with high skilled workers has already returned to trend, then longer-run forecasts may provide negative correlation between EDUcoll and the productivity response. A negative correlation between the response of productivity to a technology shock and the level of education at a forecast horizon of several years would thereby support the hypothesis that a high level of education is important for a quick adoption of new technology.

Panel A of Figure I-10 shows scatter plots for how the benchmark response functions at horizon two, three, eight and nine relate to EDUcoll. Table I-5 contains the summary correlation statistics between the factors of interest and the benchmark impulse response functions at different horizons. One year after the shock, there is a positive correlation between the state response functions and EDUcoll, while eight years after the shock the correlation has become negative. Table I-5 shows how this positive correlation changes gradually over time from positive to negative.

Horizon three and nine scatter plots for EDUhs are plotted in Panel B of Figure I-10. These plots, along with the summary correlations in Table I-5, show that indeed the share of high school educated individuals within a state is negatively correlated with the benchmark productivity responses shortly after the patent shock and positively correlated shortly after period four. Similarly, factors other than education might be important.

Following Glaeser et al. (1992) who stress the importance of industrial diversity, this chapter constructs a Dixit-Stiglitz index (similar in nature to the one constructed in Owyang et al. (2006)), Diversity, which captures the industrial diversity for each state. This variable is computed as

$$(5) \qquad Diversity_{ti} = \left(\sum_{j=1}^{20} \left(\frac{GDPS_{jit}}{GDPS_{it}} \right)^{\frac{1}{2}} \right)^{2}$$

where $GDPS_{jit}$ is GDPS in industry j and state i at time t. Twenty industries at the two digit North American Industry Classification System level are used for the data. Low values of Diversity indicate that production within state i is concentrated in a few industries; higher values indicate a more even distribution of production across sectors. Panel C of Figure I-10 shows that the period 3 productivity responses are negatively correlated with Diversity and the period 9 responses are positively correlated. The data for this variable are based on year 2000 values.

Density may also be important for explaining response function differences given that authors such as Glaeser et al. (1992) suggest that geographical proximity may help facilitate the transmission of ideas. Also, Jacobs (1969) argues that human capital externalities are best bred in dense areas. If this is the case, then denser areas might incorporate the benefits to a technology shock faster than sparsely populated regions. The period 3 scatter plot in Panel D of Figure I-10 suggests that shortly after a patent shock the productivity responses from the benchmark analysis are positively correlated with the Density variable. As described in Section I.I., this variable is measured as persons per square kilometer.

Additional non-policy variables include Manufact, which captures the share of GDPS associated with the manufacturing sector. The decline in U.S. manufacturing has received a great deal of attention in the past decade. Therefore, this chapter included the Manufact variable to make sure that this decline is not driving the results. Other non-policy variables that this chapter considers include: Union, Race, Establishment Size, and Median Age. Union contains the percentage of each state's nonagricultural wage and salary employees who belong to a union.[23] Union may be important since labor market rigidity within a state may influence the state's ability to adapt to new technologies. Race is measured by the percent of non-white individuals within a state. Average Establishment Size is perhaps a contributing factor since Griliches (1990) suggests that small firms may be more efficient at patenting with a given amount of R&D dollars. Finally, the age distribution of the state may help explain cross-state differences in productivity responses. Therefore the states' Median Ages are also examined.

Policy that is developed and implemented at the state level may also influence a state's productivity response following a technology shock. Therefore, this chapter examined Education Spending per Student, Income Tax, Corporate Tax, Property Tax per

[23] Details on data and methodology for Union are provided in Hirsch, MacPherson, and Vroman (2001).

Person, and the State Minimum Wage as explanatory variables in the cross-sectional regressions. Education Spending per Student, acquired from the National Center for Education Statistics, may proxy for the quality of grade school education. The Income Tax variable, collected from the NBER, measures the average marginal state income tax rate on wages. Corporate Tax and Property Tax were both obtained from the Tax Foundation. The former measures the highest marginal corporate income tax rate[24] and the latter estimates the average amount of property tax[25] paid by a state resident. The State Minimum Wage, provided by the BLS, is the maximum of the federally mandated minimum wage and the state specific minimum wage.

I.F.1 Benchmark Cross-Sectional Results

Chapter I now formally estimates the importance of these different demographic, economic, and policy factors at the state level by regressing the impulse responses of productivity to a technology shock at varying horizons for the 48 contiguous states on their respective state-specific economic conditions.

The collection of state economic data and impulse response functions results in cross-sectional regressions at each forecast horizon as stated in equation (2) of this chapter. The regression results from these equations are reported in Table I-6. Panels A through G of that table show the results for different mixes of the explanatory variables.

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[24] Average marginal tax rates were not available for this variable. However, since over 60% of the states have a single bracket for corporate income tax, lacking average marginal rates should not be an issue.
[25] Since property taxes are collected at the county level, then for each state this variable aggregates total property taxes across all counties and divides by the total state population.

A constant is included in all equations.[26] The table reports the coefficient estimates along with their associated standard errors and T-statistics. Significance is indicated by stars.

Panel A of Table I-6 reports how EDUhs is significantly negative at the short-run forecast horizon but in the long run becomes significantly positive. In Table I-6, Panel B, EDUhs enters insignificantly negative in the short run and significantly positive in the long run. This result supports the finding that states with a relatively low-skilled population can experience a temporary slowdown in productivity growth shortly after a technology shock but then later will see the positive effects of the given new technology.

The education indicator in Table I-6, Panel A, only includes the share of state population with at least a high school degree but not a college degree. However, skilled labor is expected also to be important in the adoption of new technology. Panel B and C of Table I-6 therefore additionally include EDUcoll. In both tables, EDUcoll enters significantly positively in the short run, indicating how skilled labor is valuable after the initial arrival of new technology. At the long horizon of Table I-6, Panel B, EDUcoll becomes insignificantly negative. As explained above, this is likely do to the trend stationarity of the variables. An alternative explanation is that skilled labor is particularly important initially after a technology shock in order to incorporate the new technology into the production function. However, once this has happened and low-skilled workers can take over, the high-skilled workers can be moved into the development of new products that may in the future lead to new technology but which at the present time does

[26] Results not shown indicate that region-specific constants are not important. To avoid unnecessary loss of degrees of freedom, a single constant is included instead.

not result in immediate productivity gains. However, these negative results are very insignificant.

This chapter also tried in Panel D of Table I-6 to include as an education factor the share of state population with at least a high school degree. This variable is therefore the combined effect of EDUhs and EDUcoll. The analysis shows that the short-run positive effects of high-skilled labor tend to dominate as EDUalhs has a significantly positive coefficient during a few periods following the technology shock.

Diversity is negatively correlated with the response of productivity to a technology shock at the short-run forecast horizon. This means that states that are more specialized are more likely to obtain short-run positive productivity gains than states that are more diverse. This result is consistent with theories that predict that knowledge spillovers within industries are more important than spillovers across industries. In addition, Table I-6, Panel A, shows that Manufact is insignificant for all forecast horizons. This result is consistent across the cross-sectional regression analyses performed in this chapter. Therefore, other results that include Manufact are not shown.

Panels C and D of Table I-6 show that Density enters significantly positively during the first periods after the shock but becomes significantly negative at the long forecast horizon. This result shows that a densely populated area experiences a more positive productivity response soon after a technology shock. One explanation for this result arises if knowledge spillovers are best fostered in dense areas.

The importance of Union, Income Tax, and Median Age are analyzed in Panels E through G of Table I-6. These tables consistently include EDUcoll, Diversity, and Density. However, the fourth covariate is Union, Income Tax, or Median Age, depending on the regression. Though Panel E shows that union membership is negatively correlated with the long-run productivity responses, the results are highly insignificant for all forecast horizons indicating that labor market rigidity is not important when explaining cross-state productivity response functions. The results from Panel F show that Income Tax is also insignificant at all forecast horizons.[27] Similarly, Panel G shows that Median Age is unimportant, though positively correlated with the benchmark productivity response functions.

A more careful analysis of the effect of the age distribution on the productivity responses has also been performed, although the tables are not reported in this chapter. Most strata of the age distribution were not important in explaining the productivity response functions. However, the under-18 layer was significant and negatively correlated at horizons three and four.[28] In addition, the portion of the distribution aged 25 to 44 was significant and positively correlated with the responses at short horizons. This result suggests that states with a relatively youthful working-age population (25 to 44) will initially respond more positively to a technology shock than states with a smaller share.

In results not shown, Establishment Size, Education Spending, Race, Corporate Tax, Property Tax, and Minimum Wage were also included one at a time in an estimating equation with EDUcoll, Diversity, and Density. However, these variables did not change the regression results reported in Table I-6, Panel C. Moreover, these variables were not significantly different from zero.

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[27] This chapter also preformed the regression analysis while excluding those states that have zero income taxes. Under that restricted sample Income Tax was also insignificant.

[28] For period 3 the population under the age of 18 is significant at the 5% level and for period 4 it is significant at the 10% level.

On the importance of the covariates analyzed in this chapter, the inclusion of the education, industry diversity, and density variables, among others, leads to R^2 values of close to 40% in Table I-6, Panel C, at the 3 year horizon. Additionally, later in the forecast horizon, period 9 and 10, the covariates account for nearly 33% of the variation. These variables can therefore account for a considerable amount of the fluctuation in the response of productivity to a patent shock, providing further confidence in the results.

I.F.2 Robustness of the Cross-Sectional Results

I.F.2.1 Excluding Oil States

Value added in a few states in the sample comes to a large extent from the oil industry. Measured labor productivity growth in these states may be confounded by changes in the price of oil. To take this into account, this chapter re-estimated the equations of interest while excluding states from the cross-sectional analysis that have a share of mining value added that is in excess of 5%. Therefore, the states of Louisiana, New Mexico, Oklahoma, Texas, West Virginia, and Wyoming were excluded.[29]

The results from estimating the cross-sectional equations with the reduced sample are reported in Table I-8 of this chapter's Appendix. The overall education results from excluding the six oil producing states are unchanged. In particular, Panels A and B of Table I-8 show that EDUhs continues to have coefficients that are significantly negative in the short run and significantly positive in the long run. Also, Panels B and C of Table I-8 show that EDUcoll has significantly positive correlation with the response of productivity during the short-run forecast horizon.

[29] Figure I-19 of the appendix shows a map of these states.

Industrial diversity continues to be negatively correlated and have some importance in explaining the short-run response of productivity to a technology shock. Density also maintains its explanatory power and significance in the long run. Overall this chapter of the dissertation concludes that the results are robust to leaving out the oil states from the analysis.

As additional evidence, the cross-sectional regressions were also estimated based on the impulse response functions when the relative FuelPPI was included as an exogenous variable and using the 48 benchmark states (not show). The education results were mainly unchanged, EDUcoll enters significantly positive in the short run and EDUhs enters insignificantly but positively in the long run. In the short run, industry diversity is insignificantly negatively correlated with the productivity responses. Manufact continues to have negative coefficients in the short run, however there is now one short-run period that is significant at the 10% level. The main results from the benchmark analysis are therefore considered robust to this change.

I.F.2.2 Shock to R&D

Section I.E. provided evidence that a patent shock leads to productivity responses that show positive patterns faster than if R&D is used as a measure of technological progress. The impulse response functions were overall similar in shape but were shifted along the horizontal axis. To further examine if skilled labor is important for the development and adoption of new technology, the cross-sectional analysis is now estimated based on impulse response functions from the R&D shock. The results are reported in Table I-7.

Panel A of Table I-7 shows that starting in period three, EDUhs, the share of population with only a high school degree, enters significantly negatively as an explanatory variable. Table I-7, Panel B, shows that the EDUcoll is positive and very significant throughout the forecast horizon. That is, the response of productivity to an R&D shock is highly positively correlated with the amount of skilled labor. As was the case in the patent analysis, Diversity has a significantly negative coefficient, although the timing of the significance in Table I-7, Panel A, is shifted to the middle forecast horizons. Furthermore, the regressions that include the education variables, industrial diversity, and density indeed explain 42% of the cross-state variation at period 4. Overall, the results from the R&D analysis reinforce the short-run results from the patent analysis as is expected given the lag between R&D expenditures and subsequent patent applications.

I.F.2.3 Cross-Sectional Robustness to Trivariate VARs

Section I.E.2.5 examined the robustness of the benchmark productivity response functions by including a third variable in the state-level VARs. This subsection examines the robustness of the benchmark cross-sectional results by using the productivity response functions from the trivariate analyses as dependent variables for multiple cross-sectional regressions. Table I-9 through Table I-11 of the Appendix contains the cross-sectional regression results for the trivariate productivity responses. The covariates in each regression are EDUhs, EDUcoll, Diversity, and Density. Table I-9 uses the productivity responses from the trivariate VARs where surrounding labor productivity is included as the third variable. The dependent variable from Table I-10 uses productivity responses from the trivariate VARs with employment as the third variable.[30] Table I-11 makes use of the responses that have density as the third variable.

The results in Table I-9 through Table I-11 show that EDUcoll is significantly positive at the short-run forecast horizon. Also, the coefficients on EDUhs are consistent with the results from the benchmark analysis. Diversity is negatively correlated and in some cases significant at the short-run forecast horizon, and the sign and significance of Table I-9's Density results are consistent with the benchmark analysis. However, for Tables I-10 and I-11 the significance of Density is diminished[31] because the productivity response functions have already been conditioned on population changes. Overall, the main results from the benchmark analysis are considered robust to changing the dependent variable in the cross-sectional regressions.

I.G. Conclusion

This chapter of the dissertation examined whether technological progress, measured by the number of U.S. patent applications, leads to differential effects at the state level. The chapter found that states in the Northeast region tend to see a faster increase in productivity immediately following a technology shock than do states in the Midwest. Indeed, some states are affected negatively for a few years after the shock before productivity eventually increases. When the response functions are plotted spatially for each horizon, the analysis shows that the positive effects of new technology slowly spreads across the U.S. states, starting from the coasts and moving inland.

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[30] The results from the manufacturing employment on total employment trivariate system are similar to the employment results and are therefore not reported. Also, the results that employ real GDPS as the third variable are very similar and are thus not reported.

[31] Though in Table I-11 Density is still significant at the 10% level.

Next, this chapter explored which factors are important in explaining the differential state effects of technological progress. The analysis found that education, and to some extent industrial diversity are important factors. In particular, skilled labor is very important in the short run for obtaining positive effects on productivity after the arrival of new technology. In addition, the density of the region is important for explaining differences in cross-state productivity responses as knowledge spillovers may indeed be best cultivated in dense regions.

The results were also estimated using R&D expenditures as an alternative measure of technological progress. The lag between R&D and subsequent patent applications is evident in the productivity response functions. The results show that skilled labor is highly important in obtaining positive effects on productivity.

I.H. Tables and Figures

Table I-1: State Productivity Growth and State Share of Gross Domestic Product

States	Productivity Growth	Share of GDP	Correlation with USA Productivity Growth	States	Productivity Growth	Share of GDP	Correlation with USA Productivity Growth
AL	1.21%	1.18%	0.73	NE	0.72%	0.57%	0.55
AZ	0.75%	1.63%	0.56	NV	0.71%	0.76%	0.60
AR	1.03%	0.69%	0.67	NH	1.79%	0.45%	0.45
CA	1.25%	13.20%	0.75	NJ	1.44%	3.54%	0.54
CO	1.31%	1.76%	0.64	NM	0.71%	0.52%	0.08
CT	1.84%	1.65%	0.54	NY	1.58%	7.97%	0.75
DE	1.55%	0.43%	0.60	NC	1.22%	2.81%	0.72
FL	1.11%	4.83%	0.53	ND	0.31%	0.18%	0.26
GA	1.48%	2.98%	0.83	OH	0.87%	3.82%	0.88
ID	0.75%	0.36%	0.26	OK	1.06%	0.92%	0.35
IL	1.20%	4.76%	0.83	OR	1.15%	1.15%	0.59
IN	0.88%	1.99%	0.84	PA	1.31%	4.00%	0.68
IA	0.67%	0.93%	0.54	RI	1.55%	0.34%	0.56
KS	0.85%	0.85%	0.58	SC	1.33%	1.15%	0.62
KY	0.44%	1.15%	0.58	SD	0.84%	0.24%	0.42
LA	1.06%	1.35%	-0.06	TN	1.33%	1.79%	0.77
ME	1.08%	0.36%	0.62	TX	1.42%	7.46%	0.38
MD	1.30%	1.85%	0.77	UT	0.85%	0.69%	0.48
MA	1.86%	2.82%	0.67	VT	1.18%	0.18%	0.44
MI	0.47%	3.46%	0.79	VA	1.31%	2.67%	0.75
MN	0.99%	1.90%	0.80	WA	0.91%	2.28%	0.45
MS	0.78%	0.66%	0.57	WV	0.63%	0.43%	0.16
MO	0.98%	1.81%	0.77	WI	0.79%	1.80%	0.79
MT	0.40%	0.22%	0.30	WY	1.01%	0.18%	-0.03

Note: The Shares of GDP columns are state shares of national GDP for the year 2000. Productivity Growth columns indicate the average annual labor productivity growth calculated over 1963-2005. The Correlation with USA Productivity Growth contains the correlation coefficient of state level labor productivity growth with aggregated state level labor productivity growth over the years 1963 to 2005.

Table I-2: ADF Test and KPSS Test

State	ADF t-Test	Result	KPSS	Result	State	ADF t-Test	Result	KPSS	Result
AL	-0.70	FR	0.11	FR	NE	-1.97	FR	0.11	FR
AZ	-0.71	FR	0.20	R	NV	-0.70	FR	0.21	R
AR	-1.15	FR	0.11	FR	NH	-1.90	FR	0.15	FR
CA	-2.00	FR	0.17	R	NJ	-2.04	FR	0.16	R
CO	-0.40	FR	0.15	R	NM	-3.00	FR	0.06	FR
CT	-2.10	FR	0.18	R	NY	-1.41	FR	0.19	R
DE	-1.30	FR	0.21	R	NC	-1.34	FR	0.19	R
FL	-0.70	FR	0.16	R	ND	-2.43	FR	0.12	FR
GA	-1.62	FR	0.19	R	OH	-1.80	FR	0.21	R
ID	-1.36	FR	0.20	R	OK	-1.23	FR	0.13	FR
IL	-1.54	FR	0.21	R	OR	-0.60	FR	0.17	R
IN	-0.48	FR	0.19	R	PA	-1.46	FR	0.18	R
IA	-0.44	FR	0.12	FR	RI	-1.67	FR	0.19	R
KS	-1.42	FR	0.10	FR	SC	-2.29	FR	0.13	FR
KY	-2.32	FR	0.15	FR	SD	-1.96	FR	0.12	FR
LA	-1.53	FR	0.13	FR	TN	-1.00	FR	0.19	R
ME	-2.13	FR	0.08	FR	TX	-0.57	FR	0.09	FR
MD	-1.50	FR	0.18	R	UT	-2.31	FR	0.09	FR
MA	-2.08	FR	0.17	R	VT	-1.51	FR	0.15	R
MI	-1.99	FR	0.22	R	VA	-0.68	FR	0.18	R
MN	-0.77	FR	0.18	R	WA	-1.17	FR	0.19	R
MS	-0.88	FR	0.13	FR	WV	-2.10	FR	0.14	FR
MO	-1.69	FR	0.17	R	WI	-1.47	FR	0.20	R
MT	-1.35	FR	0.13	FR	WY	-1.56	FR	0.12	FR

Note: The Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are performed on the logarithm of state labor productivity. Labor productivity data are calculated using a splice at 1997 to account for the changing in data definition. The abbreviations are: Fail-to-Reject the null (FR) and Reject-the-Null (R). The ADF regression equation included 2 lags of the differenced variable, a constant and time trend. The 5% critical value for the ADF test is -3.18. The KPSS test equation includes a constant and time trend, and the 5% critical value is 0.15.

Table I-3: Correlation between R&D Growth and Patent Growth

h	$Corr\left(\Delta \log\left(RandD_t\right), \Delta \log\left(PAT_{t+h}\right)\right)$
-2	0.090
-1	0.150
0	0.251
1	0.308
2	0.379
3	0.409
4	0.363

Note: The contemporaneous correlation is taken using growth data from 1964 to 2004. The sample sizes of the asynchronous correlations are shorter depending on the value of h.

Table I-4: Cross-Sectional Summary Statistics

Variable	Mean	Median	St. Dev.	Min	Max
Average Establishment Size	15	15	2	9	19
High School Education	58.1%	58.1%	4.1%	50.2%	66.0%
College Education	23.7%	23.1%	4.4%	14.8%	33.2%
At Least High School Education	81.8%	82.1%	4.3%	72.9%	88.0%
Education Spending per Student	$7,216	$6,934	$1,428	$4,674	$11,248
Industrial Diversity	16.4	16.5	0.6	14.2	17.3
Non-white Population	17.5%	14.9%	10.1%	2.1%	38.1%
Union Membership	12.0%	11.4%	5.3%	3.7%	25.7%
Manufacturing share of GDP-S	15.0%	13.9%	5.5%	3.8%	29.8%
Persons per Square KM	62	32	82	2	373
Population	5,828,809	4,187,966	6,258,856	494,139	34,002,756
Income Tax	4.5%	5.0%	2.4%	0.0%	8.7%
Corporate Tax	6.5%	7.0%	3.0%	0.0%	12.0%
Property Tax per Person	$963	$952	$382	$342	$1,948
State Minimum Wage	$5.29	$5.15	$0.35	$5.15	$6.50
Median Age	35.6	35.9	1.9	27.1	38.9

Note: The data are year 2000 values. Industrial Diversity is a Dixit-Stiglitz index of 2-digit NAICS GDP-S. Income Tax data is the average marginal tax rate for wages from the NBER. Corporate Tax is the highest marginal corporate income tax rate. Property Tax measures the average property tax burden for individuals within a given state. State Minimum Wage is the maximum of the federal minimum wage and the state minimum wage. St. Dev. is the standard deviation.

Table I-5: Correlation between Productivity Responses and Explanatory Variables

Forecast Horizon(h)	1	2	3	4	5	6	7	8	9	10
Average Est. Size	0.16	0.09	0.07	0.03	0.01	-0.07	-0.03	0.06	0.08	0.09
H.S. Education	-0.30	-0.33	-0.29	-0.11	0.02	0.18	0.32	0.36	0.39	0.40
College Edu.	0.28	0.43	0.44	0.28	0.16	0.10	-0.01	-0.09	-0.14	-0.20
At Least H.S. Edu.	0.00	0.12	0.17	0.18	0.19	0.27	0.30	0.25	0.22	0.18
Education $/Student	0.31	0.40	0.48	0.36	0.18	0.04	-0.15	-0.28	-0.32	-0.35
Industrial Diversity	-0.33	-0.27	-0.33	-0.35	-0.26	-0.14	0.07	0.23	0.28	0.29
Non-white Pop.	0.14	0.08	0.00	-0.07	-0.09	-0.17	-0.21	-0.16	-0.13	-0.10
Union Membership	0.24	0.29	0.33	0.29	0.19	0.07	-0.12	-0.26	-0.31	-0.33
Manufact Share	0.09	-0.07	0.02	0.17	0.20	0.15	0.02	-0.12	-0.16	-0.15
Density	0.49	0.54	0.53	0.38	0.20	-0.03	-0.35	-0.52	-0.57	-0.57
Population	0.25	0.26	0.21	0.20	0.16	0.04	-0.16	-0.24	-0.25	-0.24
Income Tax	0.18	0.05	0.09	0.08	0.02	-0.01	-0.03	-0.06	-0.07	-0.09
Corporate Tax	0.15	0.07	0.12	0.05	-0.05	-0.06	-0.12	-0.22	-0.25	-0.26
Property Tax	0.24	0.39	0.48	0.34	0.15	-0.01	-0.18	-0.28	-0.33	-0.35
Minimum Wage	0.10	0.26	0.25	0.22	0.17	0.13	0.04	-0.03	-0.07	-0.11
Median Age	0.11	0.15	0.27	0.26	0.17	0.13	0.09	0.00	-0.06	-0.09

Note: The cross-sectional data are from the year 2000. The impulse response function data are taken from the benchmark labor productivity response function with three lags. Industrial Diversity is a Dixit-Stiglitz index of 2-digit NAICS GDP-S. Income Tax data is the average marginal tax rate for wages from the NBER. Corporate Tax is the highest marginal corporate income tax rate. Property Tax measures the average property tax burden for individuals within a given state. Minimum Wage is the maximum of the federal minimum wage and the state minimum wage. The acronyms and abbreviations are: Establishment (Est.), High School (H.S.), Population (Pop.), Manufact (Manufacturing) and Education (Edu.).

Table I-6: Benchmark Cross-Sectional Analysis

Panel A.

h	Constant	EDUhs	Diversity	Manufact	R^2
1	**4.083***	**-0.0235**	**-0.1697**	**0.0028**	0.190
	1.459	0.011	0.082	0.009	
	2.798	-2.138	-2.070	0.323	
2	**6.620***	**-0.0387**	**-0.273**	**-0.0107**	0.189
	2.369	0.018	0.133	0.014	
	2.794	-2.172	-2.050	-0.767	
3	**8.502***	**-0.0421***	**-0.364**	**-0.0042**	0.186
	2.858	0.022	0.161	0.017	
	2.975	-1.956	-2.270	-0.253	
4	**5.09**	**-0.0127**	**-0.251**	**0.0077**	0.136
	2.137	0.016	0.120	0.013	
	2.382	-0.787	-2.095	0.615	
5	**2.5252**	**0.0012**	**-0.1387**	**0.0083**	0.082
	1.725	0.013	0.097	0.010	
	1.464	0.089	-1.432	0.823	
6	**0.7229**	**0.0124**	**-0.0634**	**0.0042**	0.060
	1.421	0.011	0.080	0.008	
	0.509	1.162	-0.794	0.505	
7	**-1.105**	**0.0212**	**0.02369**	**-0.0011**	0.108
	1.257	0.009	0.071	0.007	
	-0.879	2.238	0.336	-0.151	
8	**-2.46***	**0.0271***	**0.0913**	**-0.0067**	0.191
	1.328	0.010	0.075	0.008	
	-1.854	2.710	1.224	-0.863	
9	**-3.429**	**0.0339***	**0.130**	**-0.0097**	0.240
	1.498	0.011	0.084	0.009	
	-2.289	3.002	1.542	-1.105	
10	**-4.272**	**0.0399***	**0.161***	**-0.0102**	0.252
	1.718	0.013	0.097	0.010	
	-2.486	3.084	1.673	-1.013	

Note: h indicates the impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; Diversity is the Dixit-Stiglitz index of industrial diversity; and Manufact is the share of manufacturing in a given state. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

Table I-6 (Continued): Benchmark Cross-Sectional Analysis

Panel B.

h	Constant	EDUhs	EDUcoll	Diversity	R^2
1	**3.51****	**-0.017**	**0.01267**	**-0.176****	0.211
	1.514	0.012	0.011	0.077	
	2.320	-1.365	1.117	-2.294	
2	**3.7325**	**-0.0206**	**0.0414****	**-0.230***	0.269
	2.364	0.019	0.018	0.119	
	1.579	-1.096	2.339	-1.928	
3	**5.131***	**-0.0152**	**0.056*****	**-0.339****	0.299
	2.787	0.022	0.021	0.141	
	1.841	-0.683	2.677	-2.405	
4	**3.80***	**0.0042**	**0.0299***	**-0.270****	0.190
	2.174	0.017	0.016	0.110	
	1.750	0.243	1.837	-2.448	
5	**1.940**	**0.0122**	**0.0180**	**-0.161***	0.105
	1.790	0.014	0.013	0.090	
	1.084	0.858	1.345	-1.777	
6	**0.0366**	**0.0215***	**0.016**	**-0.073**	0.099
	1.462	0.012	0.011	0.074	
	0.025	1.846	1.465	-0.988	
7	**-1.8167**	**0.0267*****	**0.012**	**0.0297**	0.136
	1.301	0.010	0.010	0.066	
	-1.397	2.577	1.189	0.452	
8	**-3.240****	**0.0293*****	**0.0076**	**0.114**	0.187
	1.399	0.011	0.010	0.071	
	-2.316	2.624	0.727	1.612	
9	**-4.198*****	**0.0338*****	**0.0047**	**0.161****	0.222
	1.593	0.013	0.012	0.081	
	-2.635	2.664	0.394	2.001	
10	**-4.79*****	**0.0373****	**-0.0002**	**0.193****	0.234
	1.827	0.015	0.014	0.092	
	-2.622	2.561	-0.016	2.094	

Note: h indicates the impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; EDUcoll is the share of college educated within a state; and Diversity is the Dixit-Stiglitz index of industrial diversity. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

Table I-6 (Continued): Benchmark Cross-Sectional Analysis

Panel C.

h	Constant	EDUhs	EDUcoll	Diversity	Density	R^2
1	**0.1756**	**0.0058**	**0.0120**	**-0.0732**	**0.11175****	0.277
	2.228	0.016	0.011	0.090	0.056	
	0.079	0.357	1.091	-0.811	1.988	
2	**-3.1295**	**0.0251**	**0.0400****	**-0.0199**	**0.2298*****	0.376
	3.359	0.024	0.017	0.136	0.085	
	-0.932	1.029	2.417	-0.146	2.712	
3	**-2.9042**	**0.0384**	**0.0542*****	**-0.0923**	**0.2691*****	0.400
	3.965	0.029	0.020	0.161	0.100	
	-0.732	1.334	2.775	-0.575	2.691	
4	**-1.1067**	**0.0369**	**0.0289***	**-0.1184**	**0.1645****	0.262
	3.192	0.023	0.016	0.129	0.081	
	-0.347	1.595	1.838	-0.916	2.042	
5	**-0.6603**	**0.0296**	**0.0175**	**-0.0810**	**0.0871**	0.138
	2.702	0.020	0.013	0.109	0.068	
	-0.244	1.508	1.314	-0.741	1.278	
6	**-0.4126**	**0.0245**	**0.0160**	**-0.0592**	**0.0150**	0.100
	2.247	0.016	0.011	0.091	0.057	
	-0.184	1.503	1.441	-0.651	0.265	
7	**0.1166**	**0.0138**	**0.0120**	**-0.0296**	**-0.0647**	0.169
	1.962	0.014	0.010	0.079	0.049	
	0.059	0.971	1.239	-0.372	-1.308	
8	**0.4325**	**0.0048**	**0.0084**	**0.0014**	**-0.123****	0.284
	2.019	0.015	0.010	0.082	0.051	
	0.214	0.326	0.841	0.017	-2.415	
9	**0.2468**	**0.0042**	**0.0056**	**0.0248**	**-0.1489*****	0.327
	2.279	0.017	0.011	0.092	0.057	
	0.108	0.254	0.500	0.269	-2.589	
10	**-0.0466**	**0.0057**	**0.0008**	**0.0479**	**-0.1589****	0.324
	2.640	0.019	0.013	0.107	0.067	
	-0.018	0.295	0.058	0.448	-2.385	

Note: h indicates the impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; EDUcoll is the share of college educated within a state; Diversity is the Dixit-Stiglitz index of industrial diversity; and Density is the persons per square kilometer. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

Table I-6 (Continued): Benchmark Cross-Sectional Analysis

Panel D.

h	**Constant**	**EDUalhs**	**Diversity**	**Density**	R^2
1	**-0.3219**	**0.0105**	**-0.0606**	**0.1267*****	0.275
	1.782	0.010	0.083	0.040	
	-0.181	1.033	-0.730	3.200	
2	**-4.3239**	**0.0365****	**0.0104**	**0.2657*****	0.370
	2.694	0.015	0.126	0.060	
	-1.605	2.373	0.082	4.440	
3	**-4.1719**	**0.0505*****	**-0.0602**	**0.3072*****	0.396
	3.177	0.018	0.148	0.071	
	-1.313	2.785	-0.407	4.353	
4	**-0.4636**	**0.0308****	**-0.1347**	**0.1451****	0.260
	2.552	0.015	0.119	0.057	
	-0.182	2.118	-1.132	2.559	
5	**0.3069**	**0.0204***	**-0.1055**	**0.0580**	0.130
	2.167	0.012	0.101	0.048	
	0.142	1.649	-1.045	1.205	
6	**0.2719**	**0.0180***	**-0.0765**	**-0.0055**	0.095
	1.800	0.010	0.084	0.040	
	0.151	1.753	-0.913	-0.139	
7	**0.2646**	**0.0124**	**-0.0333**	**-0.0692****	0.169
	1.567	0.009	0.073	0.035	
	0.169	1.390	-0.456	-1.988	
8	**0.1447**	**0.0075**	**0.0086**	**-0.1144*****	0.283
	1.613	0.009	0.075	0.036	
	0.090	0.816	0.115	-3.190	
9	**0.1334**	**0.0053**	**0.0277**	**-0.1454*****	0.327
	1.820	0.010	0.085	0.040	
	0.073	0.508	0.327	-3.597	
10	**0.3460**	**0.0019**	**0.0380**	**-0.1707*****	0.323
	2.110	0.012	0.098	0.047	
	0.164	0.160	0.386	-3.641	

Note: h indicates the impulse response function forecast horizon. EDUalhs is the share of people with at least a high school education; Diversity is the Dixit-Stiglitz index of industrial diversity; and Density is the persons per square kilometer. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.

* denotes significance at the 10 percent level.

** denotes significant at the 5 percent level.

*** denotes significance at the 1 percent level.

Table I-6 (Continued): Benchmark Cross-Sectional Analysis

Panel E.

h	Constant	EDUcoll	Diversity	Union	Density	R^2
1	**0.7898**	**0.0107**	**-0.0855**	**-0.0001**	**0.0980****	0.275
	1.448	0.011	0.085	0.009	0.042	
	0.546	1.016	-1.008	-0.006	2.329	
2	**-0.5489**	**0.0340****	**-0.0685**	**0.0028**	**0.1661*****	0.361
	2.205	0.016	0.129	0.014	0.064	
	-0.249	2.114	-0.530	0.204	2.594	
3	**0.9465**	**0.0445****	**-0.1613**	**0.0075**	**0.1678****	0.378
	2.618	0.019	0.153	0.016	0.076	
	0.362	2.325	-1.051	0.464	2.206	
4	**2.5509**	**0.0192**	**-0.1822**	**0.0087**	**0.0651**	0.226
	2.120	0.015	0.124	0.013	0.062	
	1.204	1.240	-1.466	0.670	1.057	
5	**2.3159**	**0.0100**	**-0.1347**	**0.0054**	**0.0095**	0.097
	1.794	0.013	0.105	0.011	0.052	
	1.291	0.766	-1.281	0.491	0.182	
6	**2.1137**	**0.0102**	**-0.1070**	**0.0025**	**-0.0469**	0.055
	1.494	0.011	0.088	0.009	0.043	
	1.415	0.932	-1.222	0.270	-1.080	
7	**1.6023**	**0.0091**	**-0.0598**	**-0.0006**	**-0.0973*****	0.151
	1.287	0.009	0.075	0.008	0.037	
	1.246	0.969	-0.793	-0.070	-2.604	
8	**1.0601**	**0.0081**	**-0.0153**	**-0.0040**	**-0.1297*****	0.287
	1.308	0.010	0.077	0.008	0.038	
	0.811	0.850	-0.200	-0.496	-3.413	
9	**0.8928**	**0.0060**	**0.0050**	**-0.0066**	**-0.1510*****	0.334
	1.470	0.011	0.086	0.009	0.043	
	0.607	0.560	0.058	-0.730	-3.535	
10	**0.8047**	**0.0012**	**0.0222**	**-0.0083**	**-0.1625*****	0.332
	1.702	0.012	0.100	0.010	0.049	
	0.473	0.093	0.223	-0.788	-3.287	

Note: h indicates the impulse response function forecast horizon. EDUcoll is the share of college educated individuals within a given state; Diversity is the Dixit-Stiglitz index of industrial diversity; Union is the share of the states employment that is unionized; and Density is the persons per square kilometer. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.

* denotes significance at the 10 percent level.

** denotes significant at the 5 percent level.

*** denotes significance at the 1 percent level.

Table I-6 (Continued): Benchmark Cross-Sectional Analysis

Panel F.

h	Constant	EDUcoll	Diversity	Density	IncomeTax	R^2
1	**0.6044**	**0.0096**	**-0.0772**	**0.0989****	**0.0159**	0.289
	1.423	0.010	0.083	0.040	0.017	
	0.425	0.924	-0.927	2.454	0.912	
2	**-0.4106**	**0.0349****	**-0.0755**	**0.1692*****	**-0.0047**	0.361
	2.188	0.016	0.128	0.062	0.027	
	-0.188	2.183	-0.589	2.731	-0.176	
3	**1.1435**	**0.0458****	**-0.1723**	**0.17695****	**0.0025**	0.375
	2.605	0.019	0.152	0.074	0.032	
	0.439	2.403	-1.131	2.400	0.080	
4	**2.7794**	**0.0207**	**-0.1950**	**0.0758**	**0.0031**	0.219
	2.114	0.015	0.124	0.060	0.026	
	1.315	1.340	-1.576	1.267	0.121	
5	**2.5293**	**0.0114**	**-0.1459**	**0.0157**	**-0.0042**	0.093
	1.784	0.013	0.104	0.051	0.022	
	1.418	0.875	-1.397	0.312	-0.194	
6	**2.2437**	**0.0110**	**-0.1136**	**-0.0442**	**-0.0047**	0.054
	1.483	0.011	0.087	0.042	0.018	
	1.513	1.014	-1.309	-1.052	-0.261	
7	**1.6248**	**0.0092**	**-0.0606**	**-0.0982*****	**-0.0034**	0.152
	1.276	0.009	0.075	0.036	0.016	
	1.273	0.990	-0.812	-2.719	-0.218	
8	**0.9873**	**0.0076**	**-0.0109**	**-0.1347*****	**-0.0042**	0.284
	1.301	0.010	0.076	0.037	0.016	
	0.759	0.803	-0.143	-3.660	-0.261	
9	**0.7568**	**0.0051**	**0.0131**	**-0.1593*****	**-0.0056**	0.327
	1.467	0.011	0.086	0.042	0.018	
	0.516	0.476	0.152	-3.837	-0.310	
10	**0.6443**	**0.0001**	**0.0319**	**-0.1729*****	**-0.0078**	0.324
	1.699	0.012	0.099	0.048	0.021	
	0.379	0.007	0.321	-3.597	-0.374	

Note: h indicates the impulse response function forecast horizon. EDUcoll is the share of college educated within a state; Diversity is the Dixit-Stiglitz index of industrial diversity; Density is the persons per square kilometer; and IncomeTax is the average marginal tax rate for wages. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

Table I-6 (Continued): Benchmark Cross-Sectional Analysis

Panel G.

h	Constant	EDUcoll	Diversity	Density	MedianAge	R^2
1	**0.8522**	**0.0107**	**-0.0864**	**0.0982****	**-0.0014**	0.275
	1.792	0.010	0.085	0.041	0.023	
	0.475	1.022	-1.016	2.397	-0.059	
2	**-1.2308**	**0.0351****	**-0.0620**	**0.1660*****	**0.0164**	0.363
	2.724	0.016	0.129	0.062	0.036	
	-0.452	2.211	-0.480	2.667	0.462	
3	**-1.6009**	**0.0479*****	**-0.1337**	**0.1642****	**0.0594**	0.404
	3.175	0.019	0.151	0.073	0.041	
	-0.504	2.588	-0.887	2.264	1.436	
4	**0.8020**	**0.0224**	**-0.1676**	**0.0665**	**0.0431**	0.247
	2.589	0.015	0.123	0.059	0.034	
	0.310	1.482	-1.364	1.124	1.278	
5	**1.5072**	**0.0118**	**-0.1297**	**0.0116**	**0.0208**	0.103
	2.214	0.013	0.105	0.051	0.029	
	0.681	0.915	-1.235	0.229	0.722	
6	**1.2545**	**0.0113**	**-0.0977**	**-0.0481**	**0.0200**	0.068
	1.836	0.011	0.087	0.042	0.024	
	0.683	1.058	-1.121	-1.146	0.836	
7	**0.4589**	**0.0098**	**-0.0426**	**-0.1031*****	**0.0241**	0.177
	1.568	0.009	0.074	0.036	0.020	
	0.293	1.073	-0.573	-2.878	1.181	
8	**0.0251**	**0.0080**	**0.0044**	**-0.1386*****	**0.0196**	0.297
	1.608	0.009	0.076	0.037	0.021	
	0.016	0.853	0.058	-3.774	0.934	
9	**0.0676**	**0.0052**	**0.0250**	**-0.1618*****	**0.0134**	0.331
	1.825	0.011	0.087	0.042	0.024	
	0.037	0.485	0.288	-3.879	0.563	
10	**0.1572**	**-0.0002**	**0.0416**	**-0.1743*****	**0.0085**	0.324
	2.120	0.012	0.101	0.048	0.028	
	0.074	-0.014	0.414	-3.597	0.308	

Note: h indicates the impulse response function forecast horizon. EDUcoll is the share of college educated within a state; Diversity is the Dixit-Stiglitz index of industrial diversity; Density is the persons per square kilometer; and MedianAge is the median for the age distribution with a state. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.

* denotes significance at the 10 percent level.

** denotes significant at the 5 percent level.

*** denotes significance at the 1 percent level.

Table I-7: Research and Development Cross-Sectional Analysis

Panel A.

h	Constant	EDUhs	Diversity	Manufact	R^2
1	**1.3731**	**0.0189**	**-0.1276**	**0.0151**	0.153
	1.802	0.014	0.101	0.011	
	0.762	1.390	-1.261	1.425	
2	**2.8703**	**0.0138**	**-0.1908***	**-0.0110**	0.084
	1.873	0.014	0.105	0.011	
	1.533	0.981	-1.814	-0.998	
3	**5.333*****	**-0.0232***	**-0.223****	**-0.0126**	0.173
	1.817	0.014	0.102	0.011	
	2.935	-1.693	-2.182	-1.184	
4	**6.482*****	**-0.037*****	**-0.248****	**-0.0026**	0.239
	1.883	0.014	0.106	0.011	
	3.443	-2.621	-2.348	-0.234	
5	**6.309*****	**-0.0375****	**-0.2306***	**0.0083**	0.206
	2.108	0.016	0.118	0.012	
	2.993	-2.362	-1.947	0.671	
6	**5.817*****	**-0.0319***	**-0.208***	**0.0106**	0.167
	2.165	0.016	0.122	0.013	
	2.687	-1.957	-1.712	0.834	
7	**5.101****	**-0.0248**	**-0.1782**	**0.0075**	0.118
	2.133	0.016	0.120	0.013	
	2.391	-1.546	-1.487	0.598	
8	**4.329****	**-0.0169**	**-0.1523**	**0.0034**	0.077
	2.028	0.015	0.114	0.012	
	2.135	-1.107	-1.337	0.289	
9	**3.419***	**-0.0089**	**-0.1221**	**0.0002**	0.039
	1.996	0.015	0.112	0.012	
	1.713	-0.593	-1.089	0.017	
10	**2.3618**	**-0.0006**	**-0.0867**	**-0.0019**	0.013
	2.043	0.015	0.115	0.012	
	1.156	-0.039	-0.756	-0.154	

Note: The response functions are based on a bivariate VAR with R&D and productivity. h indicates the impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; Diversity is the Dixit-Stiglitz index of industrial diversity; and Manufact is the share of manufacturing in a given state. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

Table I-7 (Continued): Research and Development Cross-Sectional Analysis

Panel B.

h	Constant	EDUhs	EDUcoll	Diversity	Density	R^2
1	**1.8402**	**0.0284**	**0.0299****	**-0.20984***	**-0.0455**	0.206
	2.821	0.020	0.014	0.114	0.071	
	0.652	1.386	2.152	-1.837	-0.639	
2	**1.3922**	**0.0218**	**0.0376*****	**-0.1850**	**-0.0401**	0.202
	2.823	0.020	0.014	0.114	0.071	
	0.493	1.066	2.702	-1.619	-0.563	
3	**1.3636**	**0.0025**	**0.0535*****	**-0.1624**	**0.0099**	0.411
	2.479	0.018	0.012	0.100	0.063	
	0.550	0.139	4.378	-1.618	0.158	
4	**2.5248**	**-0.0063**	**0.0477*****	**-0.1952***	**0.0376**	0.423
	2.650	0.019	0.013	0.107	0.067	
	0.953	-0.329	3.649	-1.820	0.563	
5	**2.0762**	**0.0006**	**0.0392****	**-0.1734**	**0.0812**	0.317
	3.159	0.023	0.016	0.128	0.080	
	0.657	0.026	2.518	-1.356	1.019	
6	**0.9209**	**0.0113**	**0.0337****	**-0.1262**	**0.1175**	0.265
	3.286	0.024	0.016	0.133	0.083	
	0.280	0.474	2.078	-0.949	1.417	
7	**-0.1331**	**0.0188**	**0.0337****	**-0.0812**	**0.1232**	0.237
	3.208	0.023	0.016	0.130	0.081	
	-0.041	0.807	2.131	-0.625	1.523	
8	**-0.3296**	**0.0205**	**0.0338****	**-0.0666**	**0.0970**	0.203
	3.047	0.022	0.015	0.123	0.077	
	-0.108	0.927	2.253	-0.540	1.262	
9	**-0.3372**	**0.0205**	**0.0335****	**-0.0583**	**0.0622**	0.153
	3.027	0.022	0.015	0.123	0.076	
	-0.111	0.932	2.244	-0.476	0.814	
10	**-0.4463**	**0.0209**	**0.0311****	**-0.0449**	**0.0318**	0.101
	3.151	0.023	0.016	0.128	0.079	
	-0.142	0.915	1.999	-0.352	0.400	

Note: The response functions are based on a bivariate VAR with R&D and productivity. h indicates the impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; EDUcoll is the share of college educated within a state; Diversity is the Dixit-Stiglitz index of industrial diversity; and Density is the persons per square kilometer. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

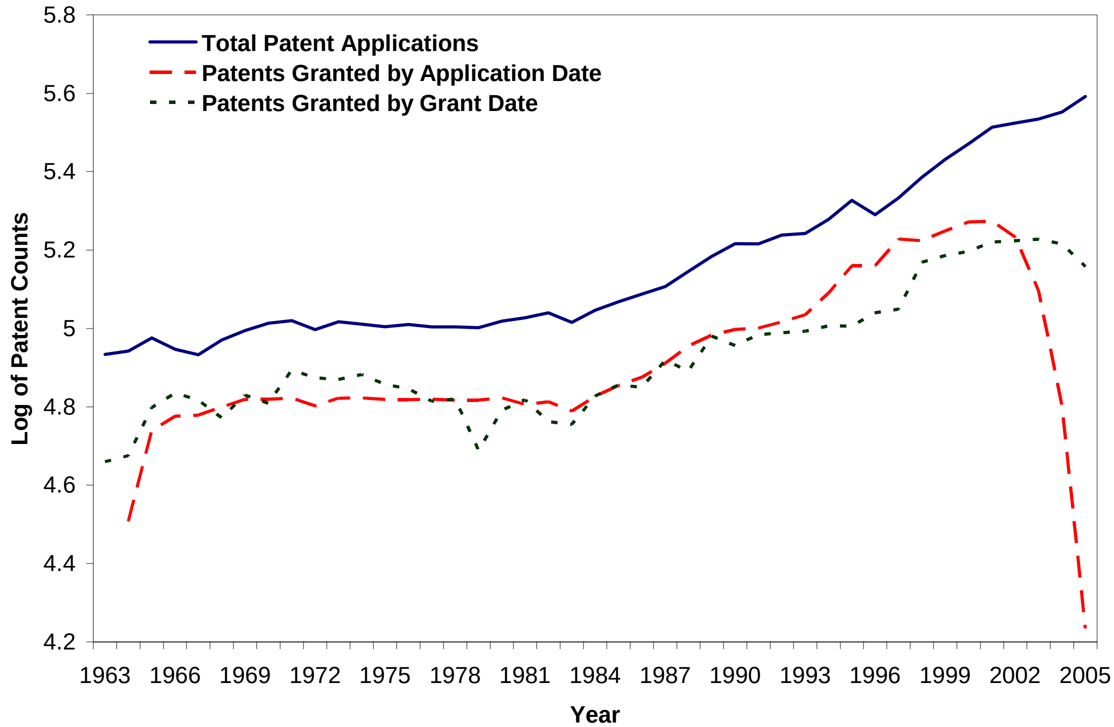


Figure I-1: Utility Patents

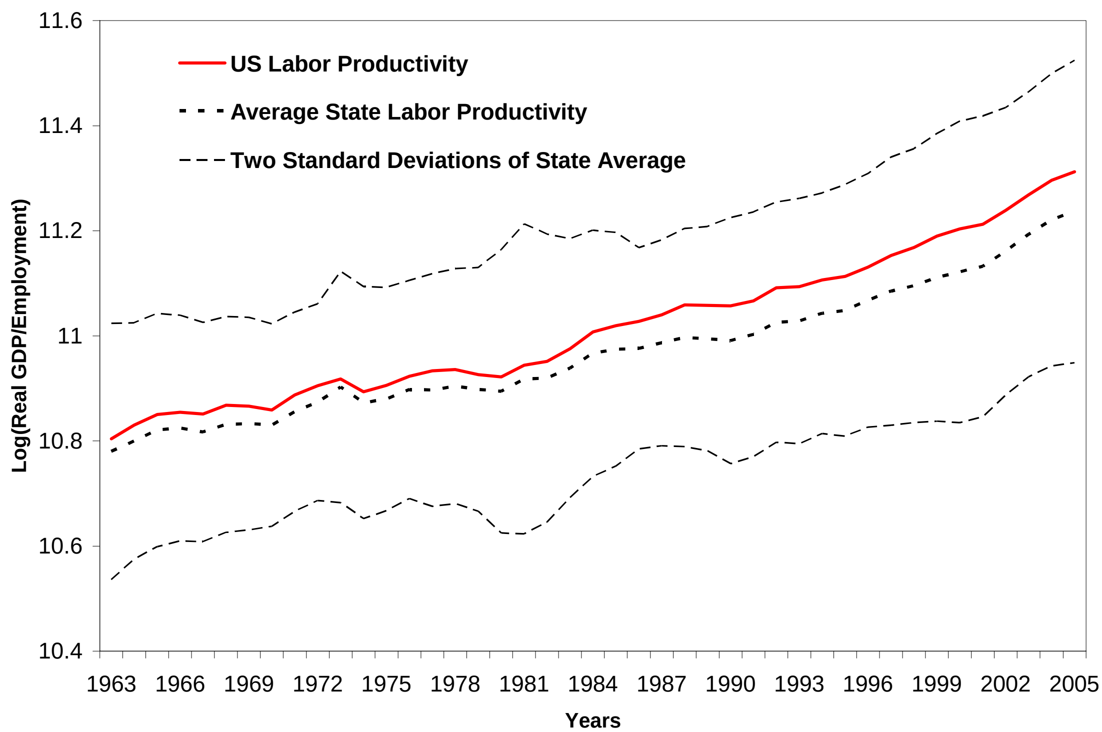
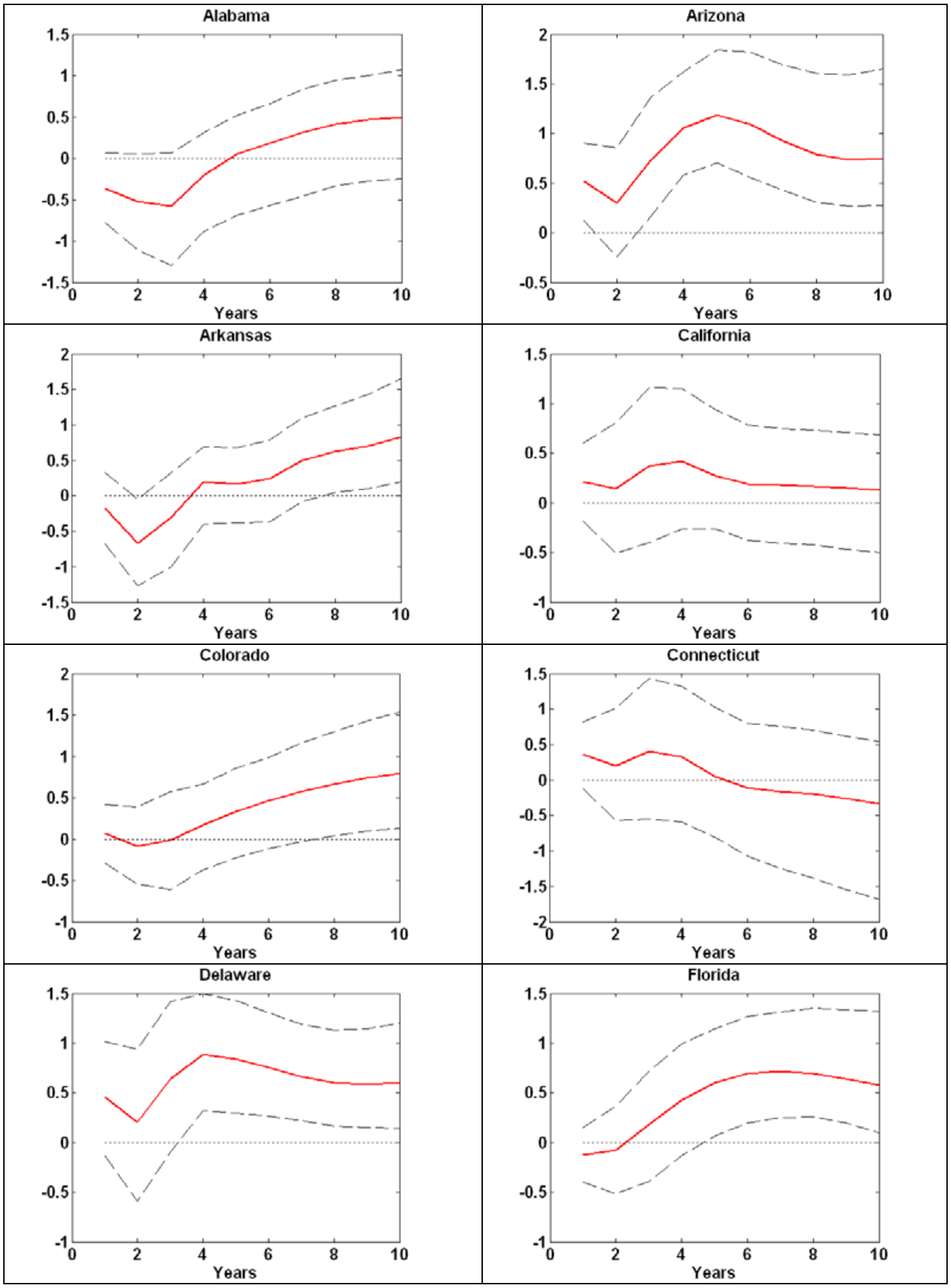
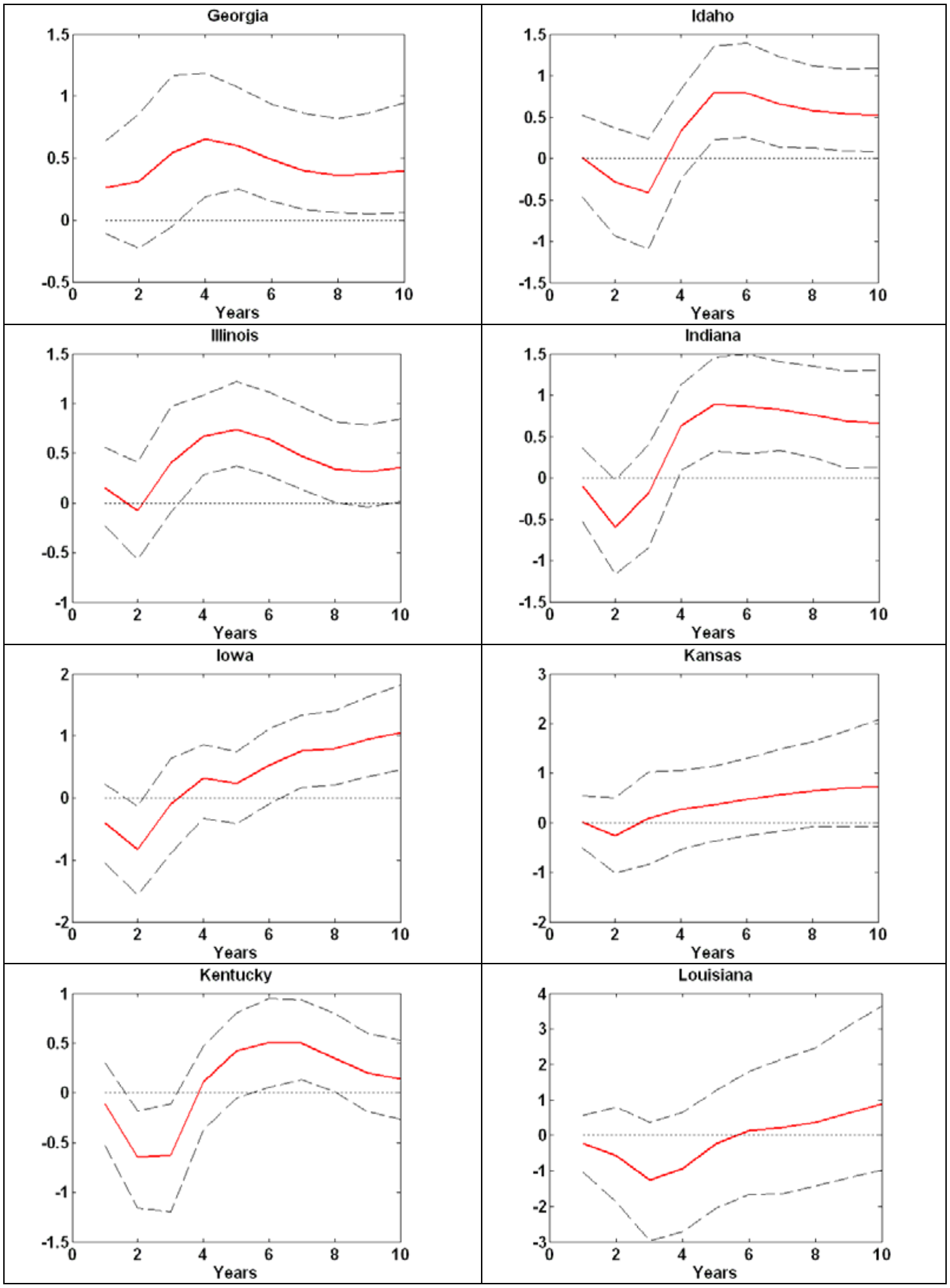


Figure I-2: Variation in State Labor Productivity around National Labor Productivity



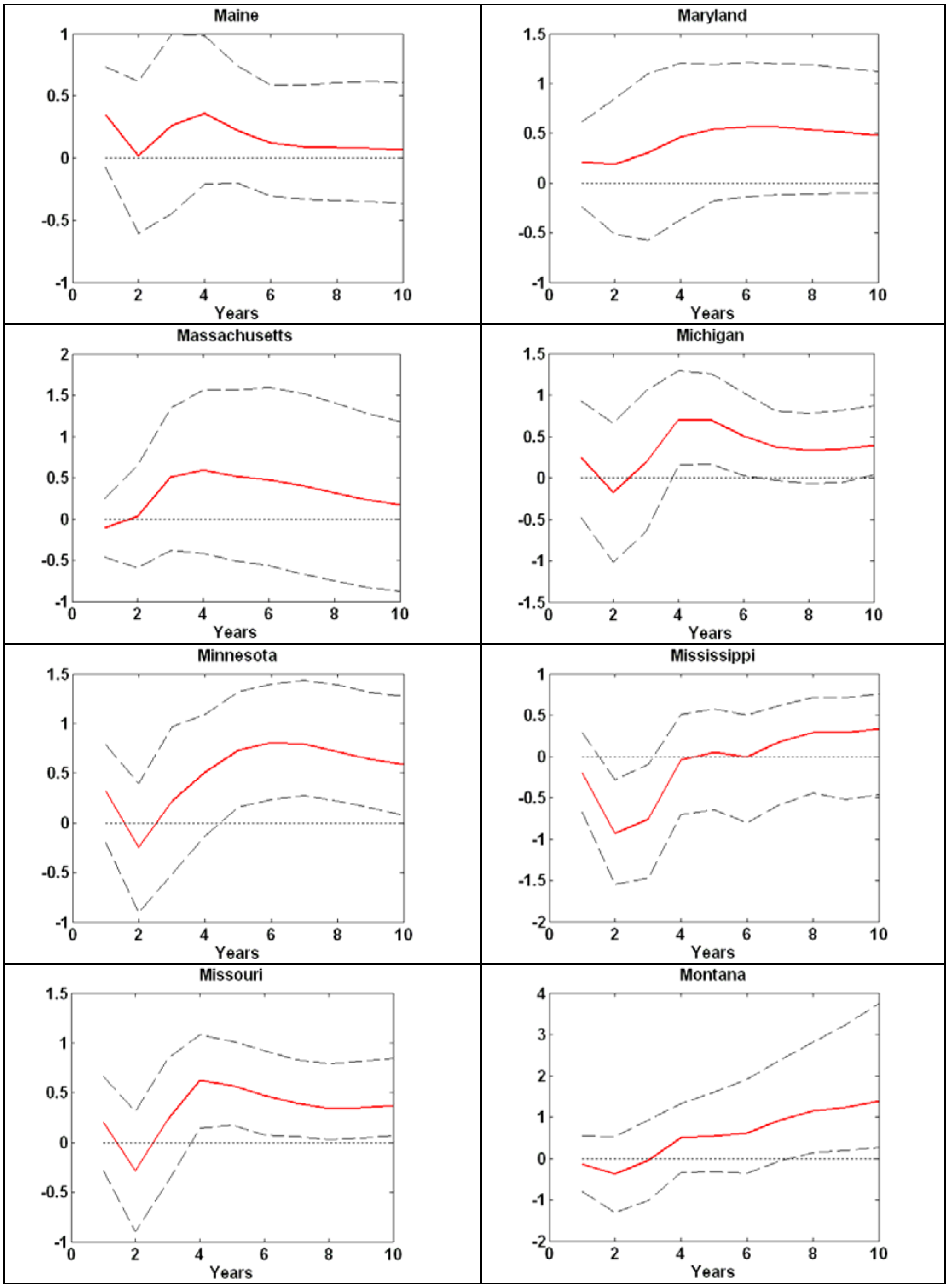
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2005.

Figure I-3: Response of Productivity to a Patent Shock



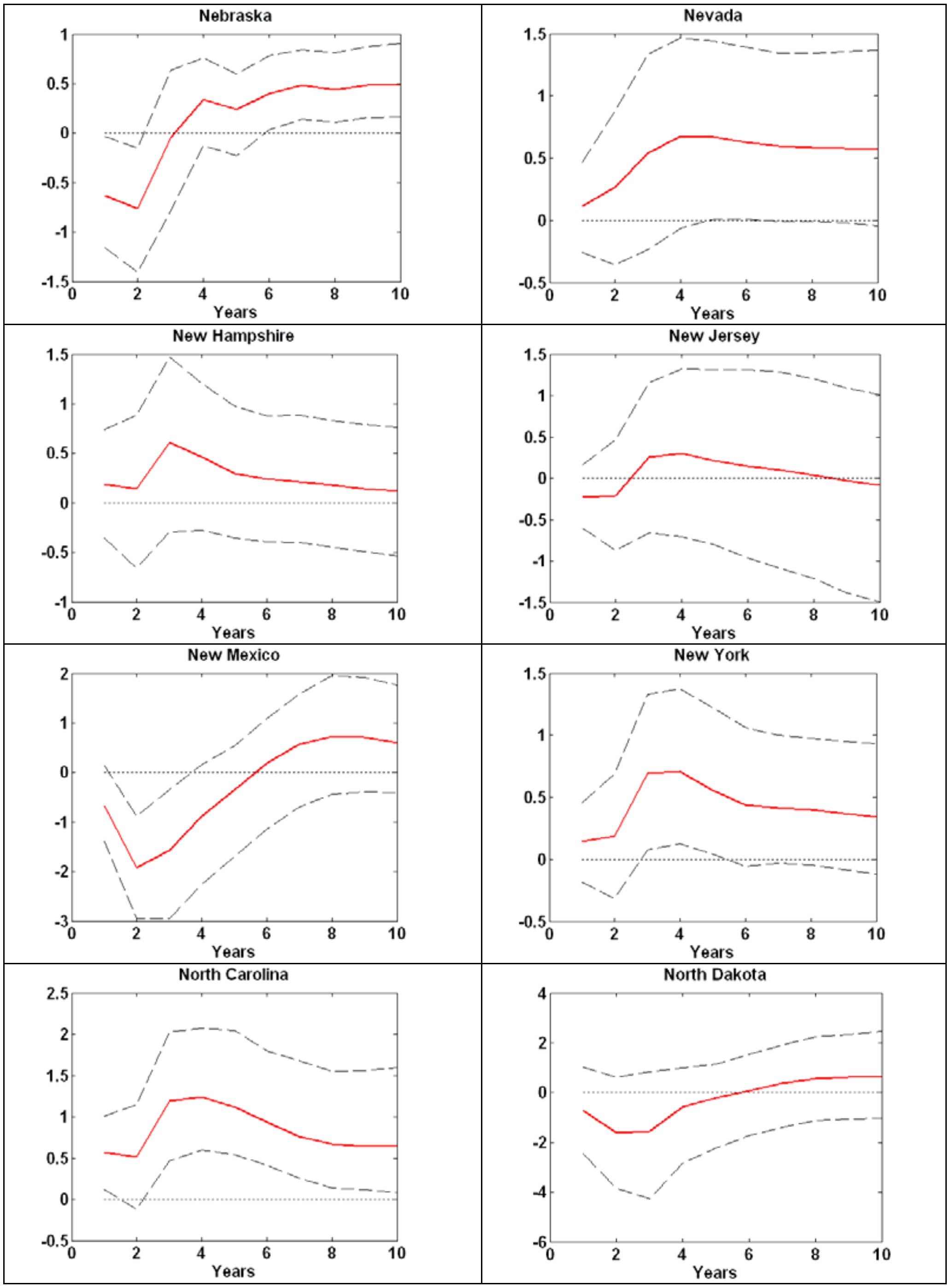
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2005.

Figure I-3 (Continued): Response of Productivity to a Patent Shock



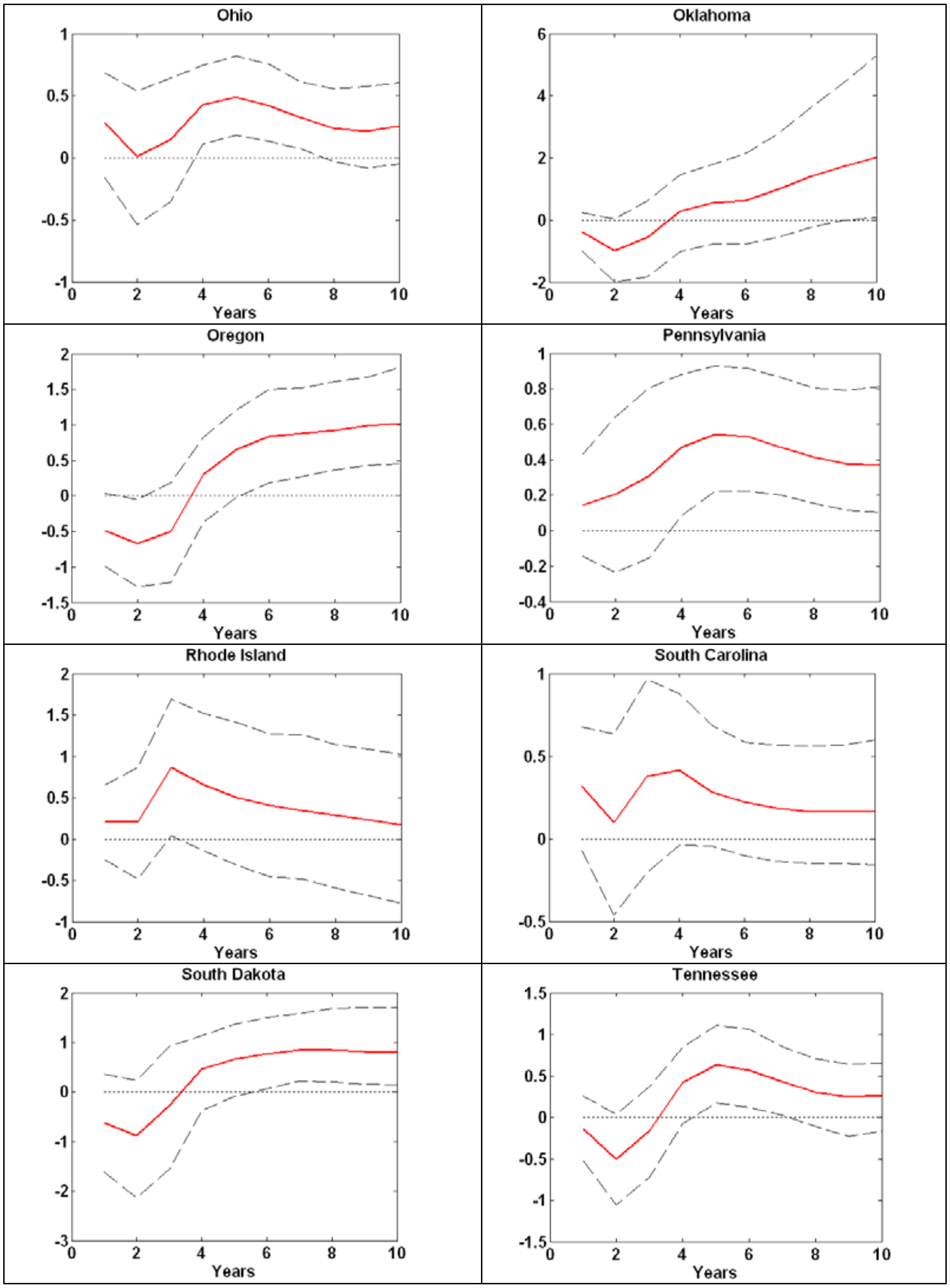
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2005.

Figure I-3 (Continued): Response of Productivity to a Patent Shock



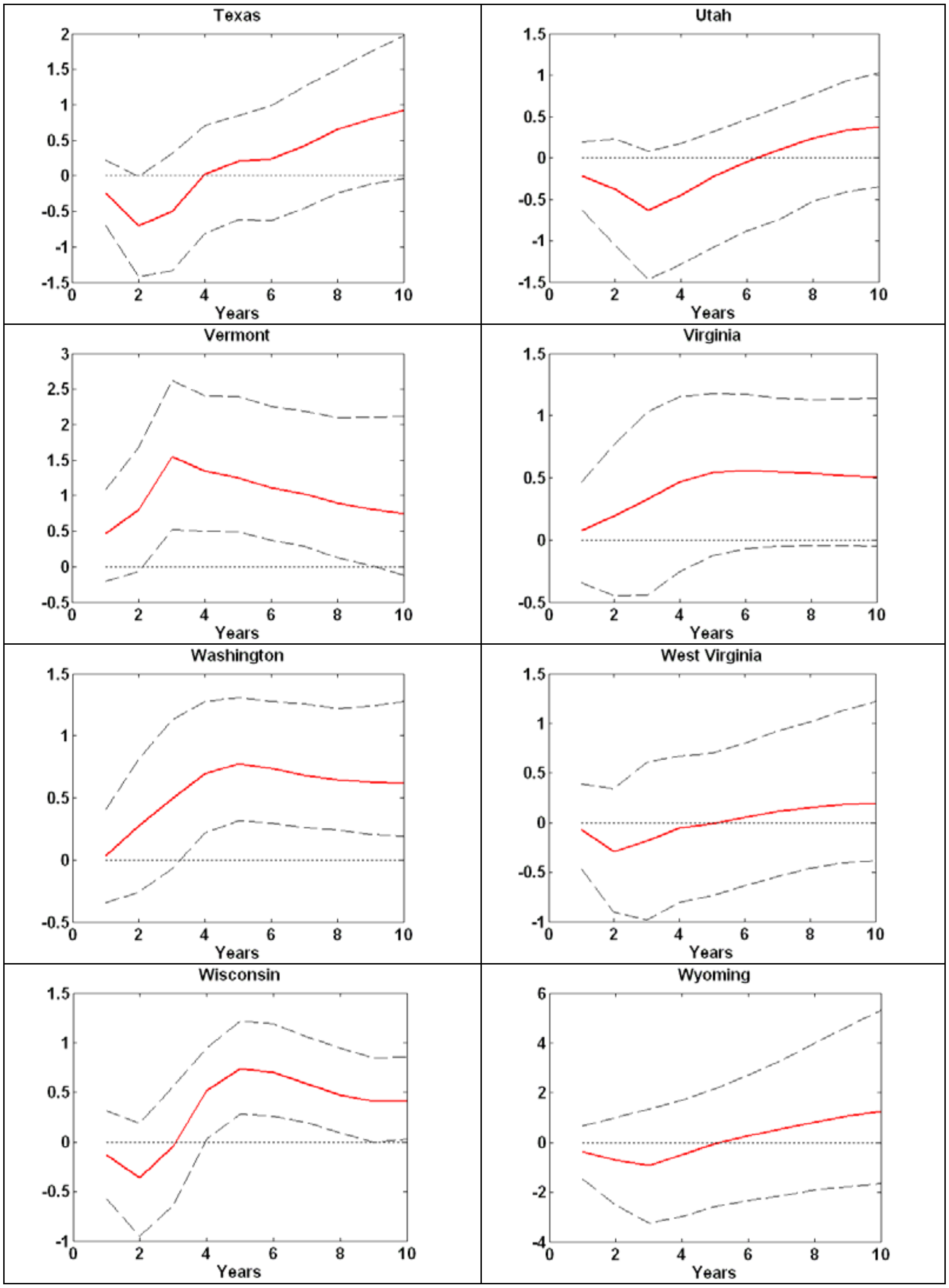
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2005.

Figure I-3 (Continued): Response of Productivity to a Patent Shock



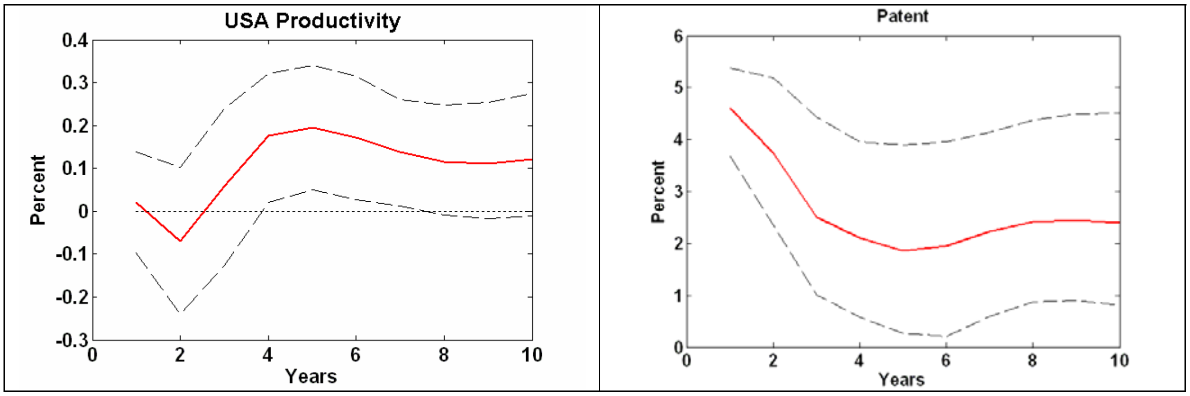
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2005.

Figure I-3 (Continued): Response of Productivity to a Patent Shock



Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2005.

Figure I-3 (Continued): Response of Productivity to a Patent Shock



Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2005.

Figure I-4: Response of Productivity and Patents to a Patent Shock, National

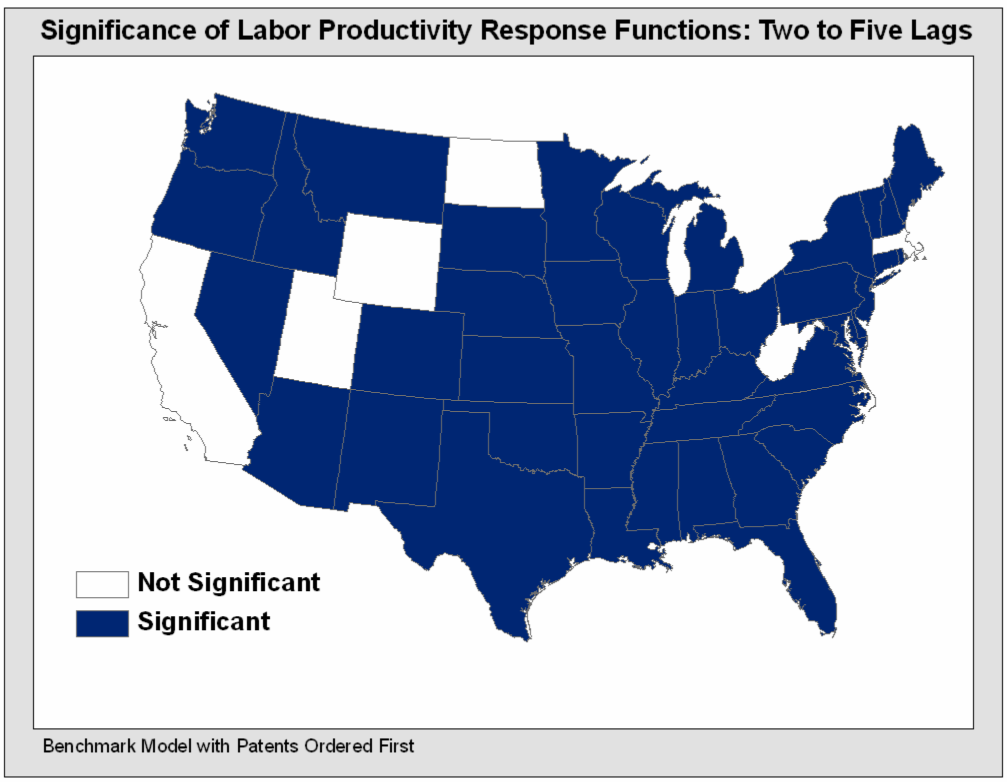
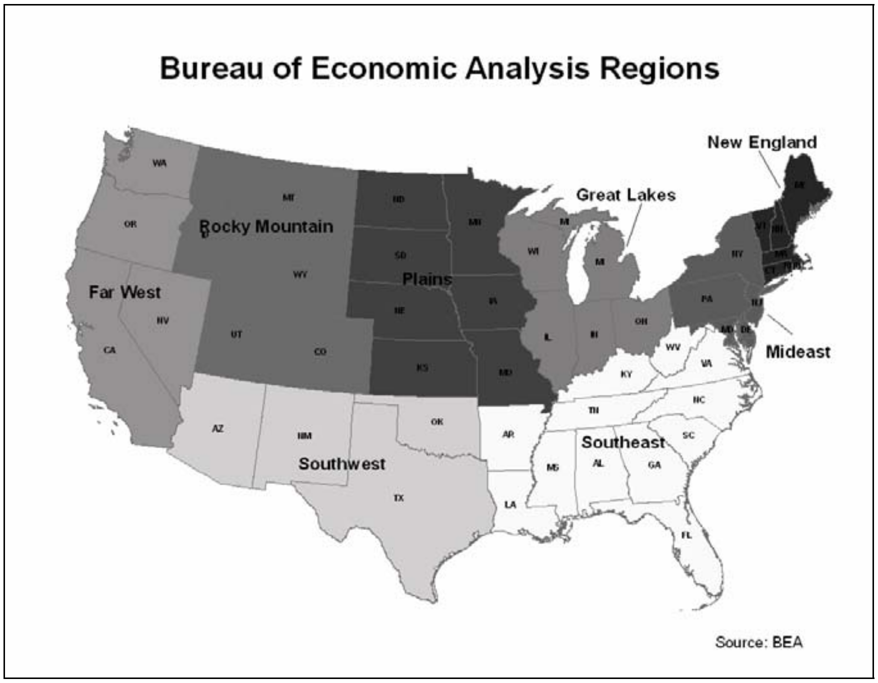
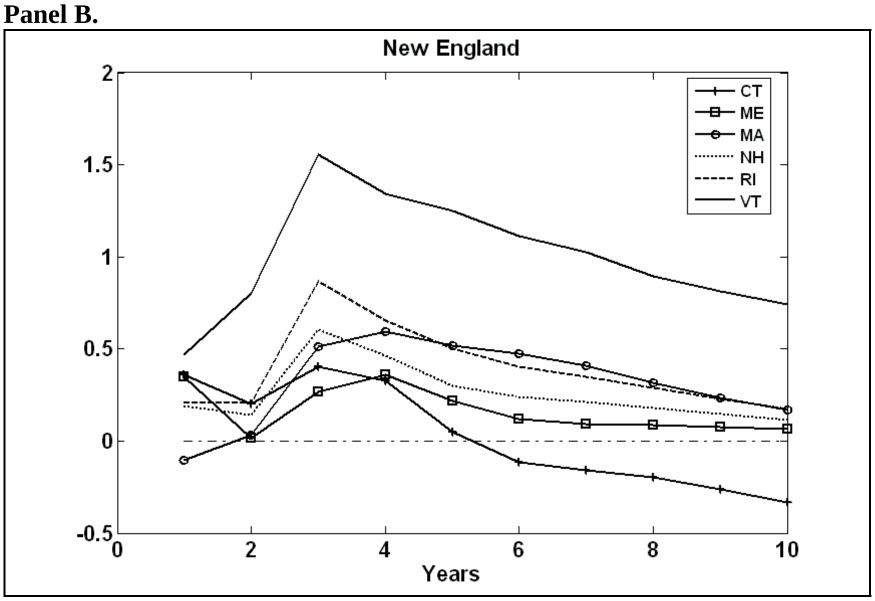


Figure I-5: Significance of the Benchmark Labor Productivity Response Functions

Panel A.



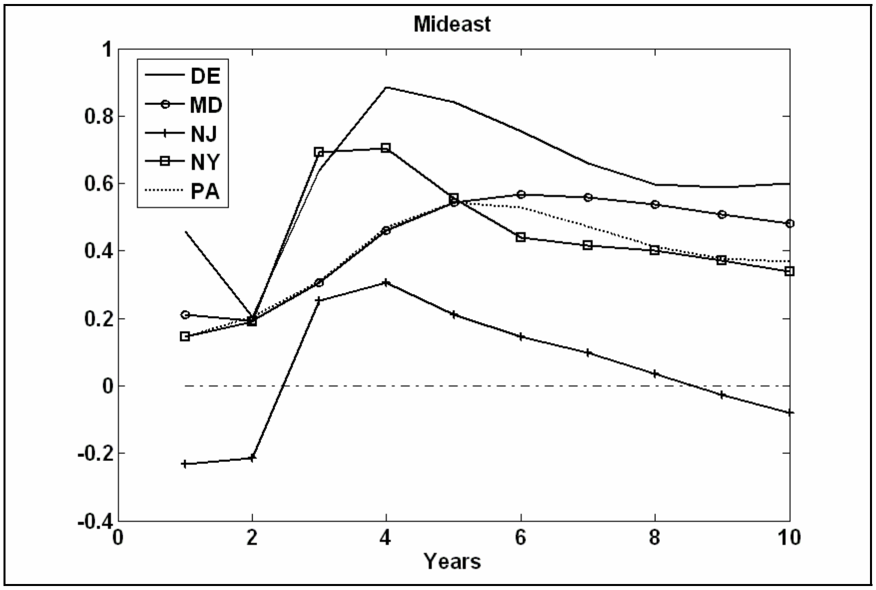
Panel B.



Note: The vertical axis indicates the percent change in the forecast of labor productivity.

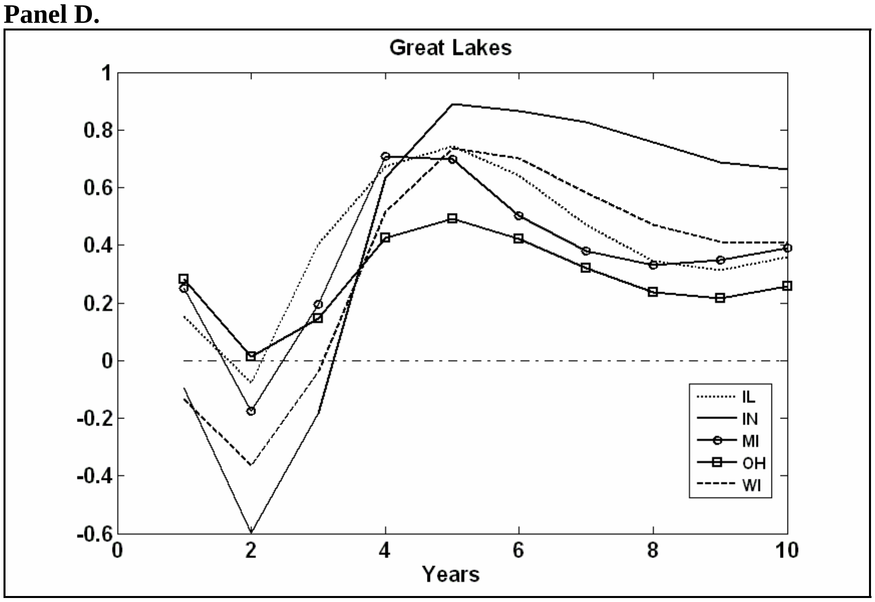
Figure I-6: Responses of Productivity to a Patent Shock, sorted by BEA regions

Panel C.



Note: The vertical axis indicates the percent change in the forecast of labor productivity.

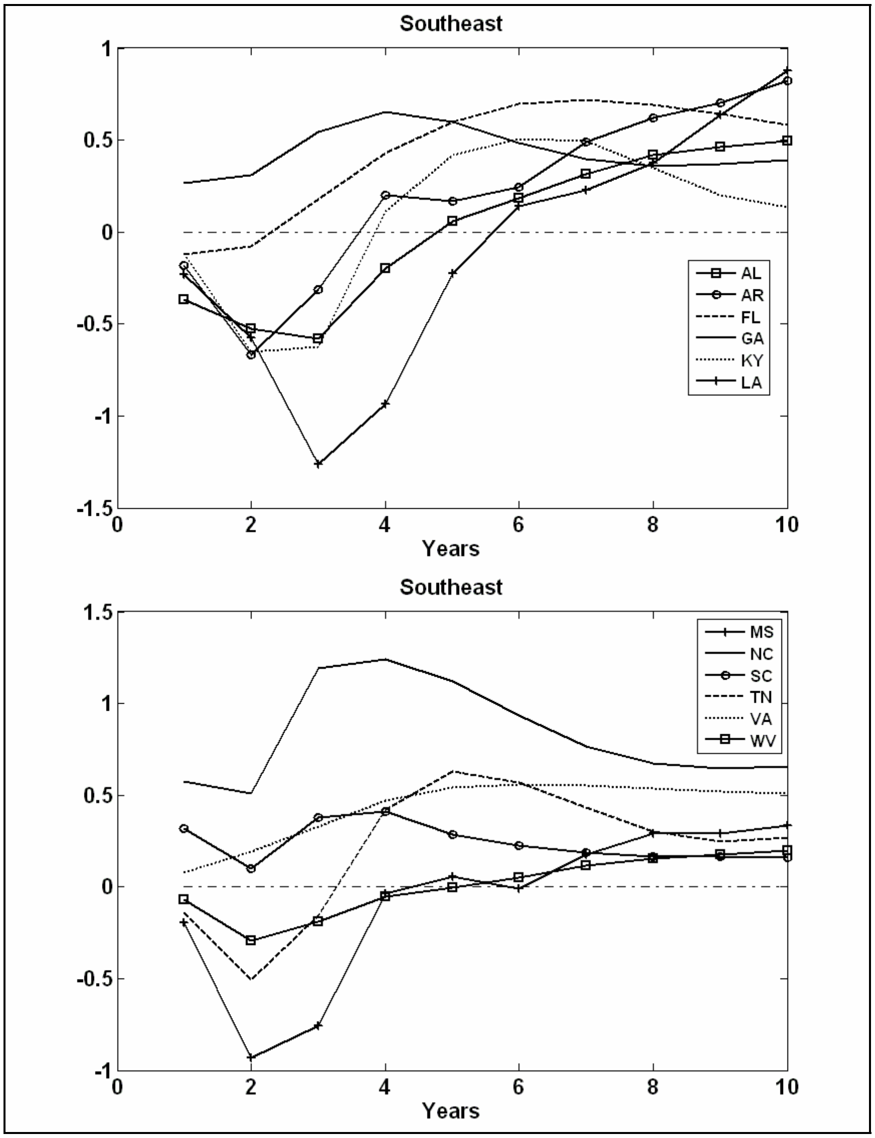
Panel D.



Note: The vertical axis indicates the percent change in the forecast of labor productivity.

Figure I-6 (Continued): Responses of Productivity to a Patent Shock, sorted by BEA regions

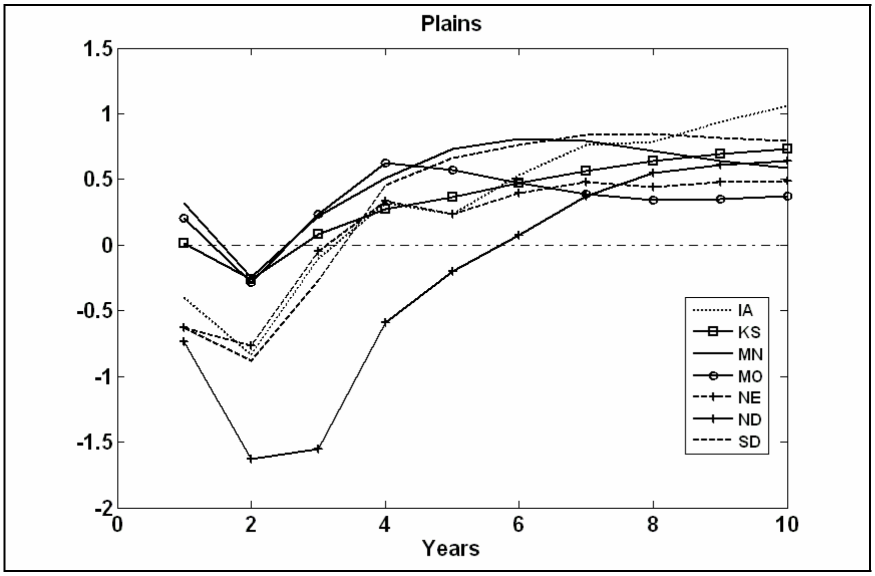
Panel E.



Note: The vertical axis indicates the percent change in the forecast of labor productivity.

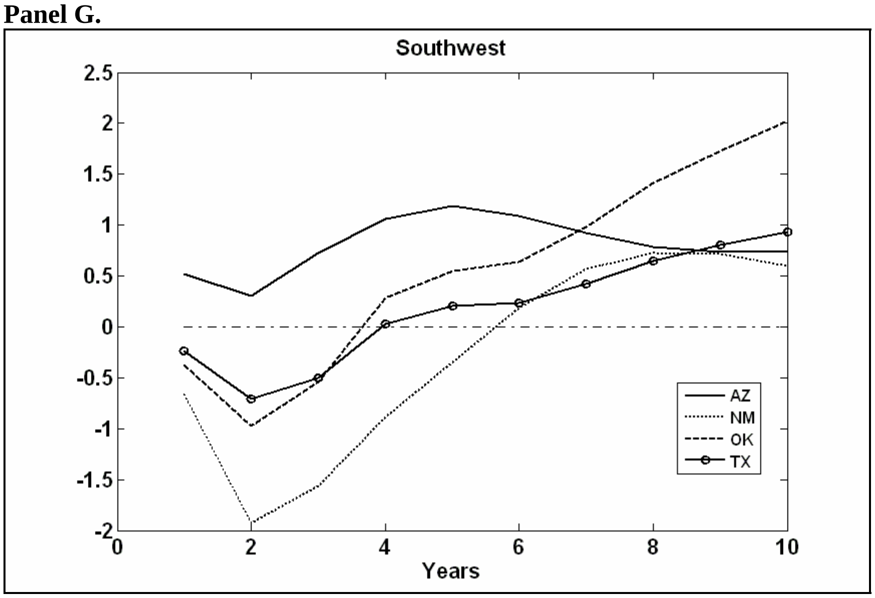
Figure I-6 (Continued): Responses of Productivity to a Patent Shock, sorted by BEA regions

Panel F.



Note: The vertical axis indicates the percent change in the forecast of labor productivity.

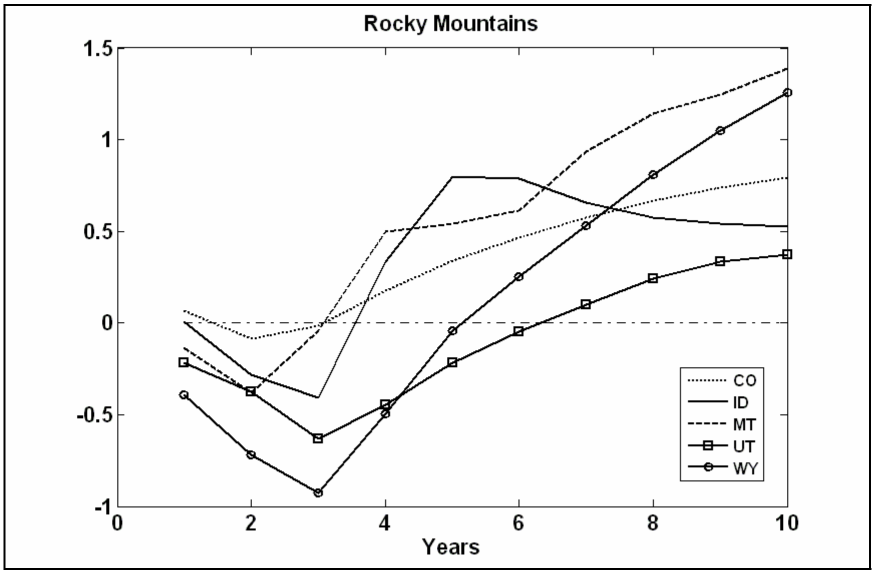
Panel G.



Note: The vertical axis indicates the percent change in the forecast of labor productivity.

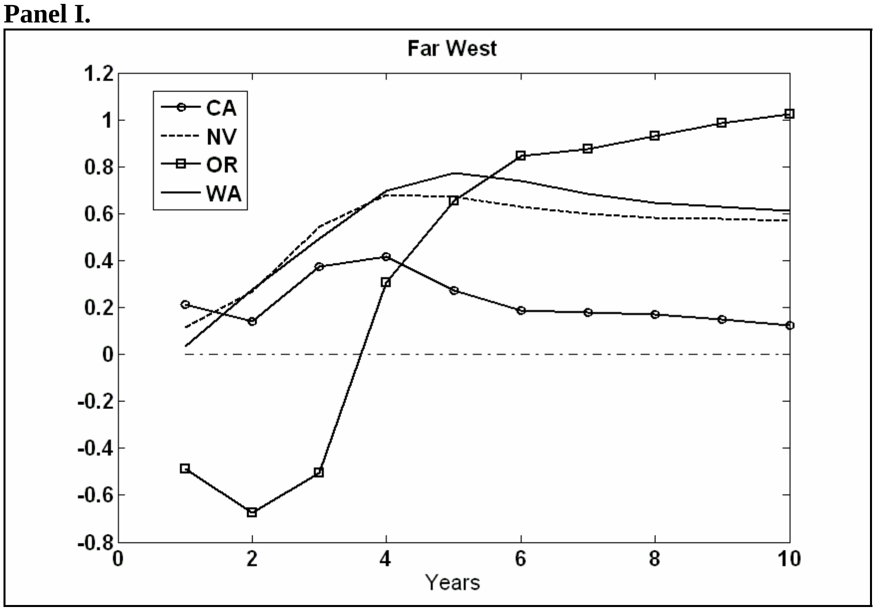
Figure I-6 (Continued): Responses of Productivity to a Patent Shock, sorted by BEA regions

Panel H.



Note: The vertical axis indicates the percent change in the forecast of labor productivity.

Panel I.



Note: The vertical axis indicates the percent change in the forecast of labor productivity.

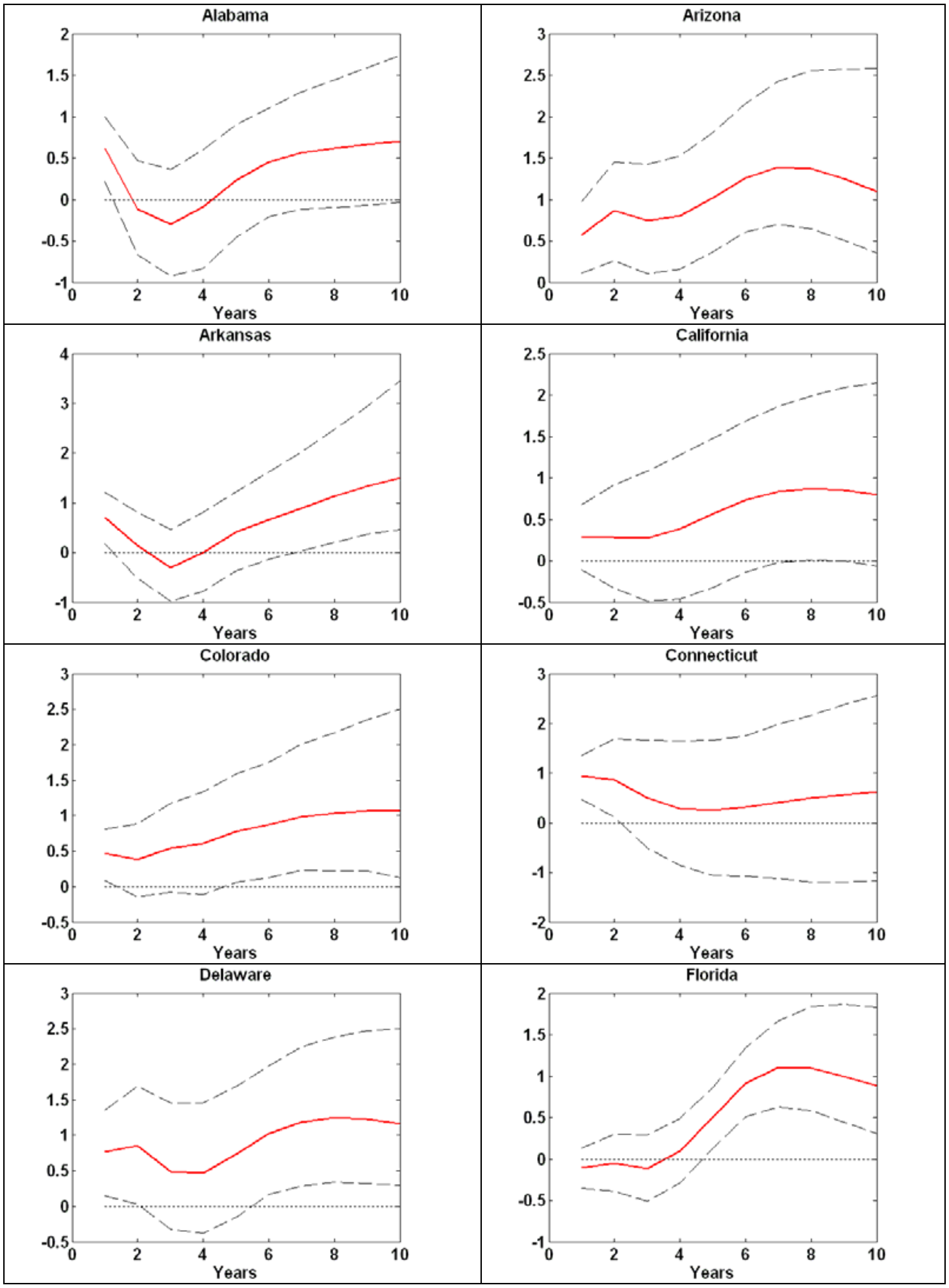
Figure I-6 (Continued): Responses of Productivity to a Patent Shock, sorted by BEA regions

Note: Period 1 is the time of the shock. The states are shaded according to the sign of the labor productivity response function: White indicates a positive response and dark grey indicates a negative response. Time Series: 1963-2005.

Figure I-7: Productivity Responses to an Aggregate Patent Shock

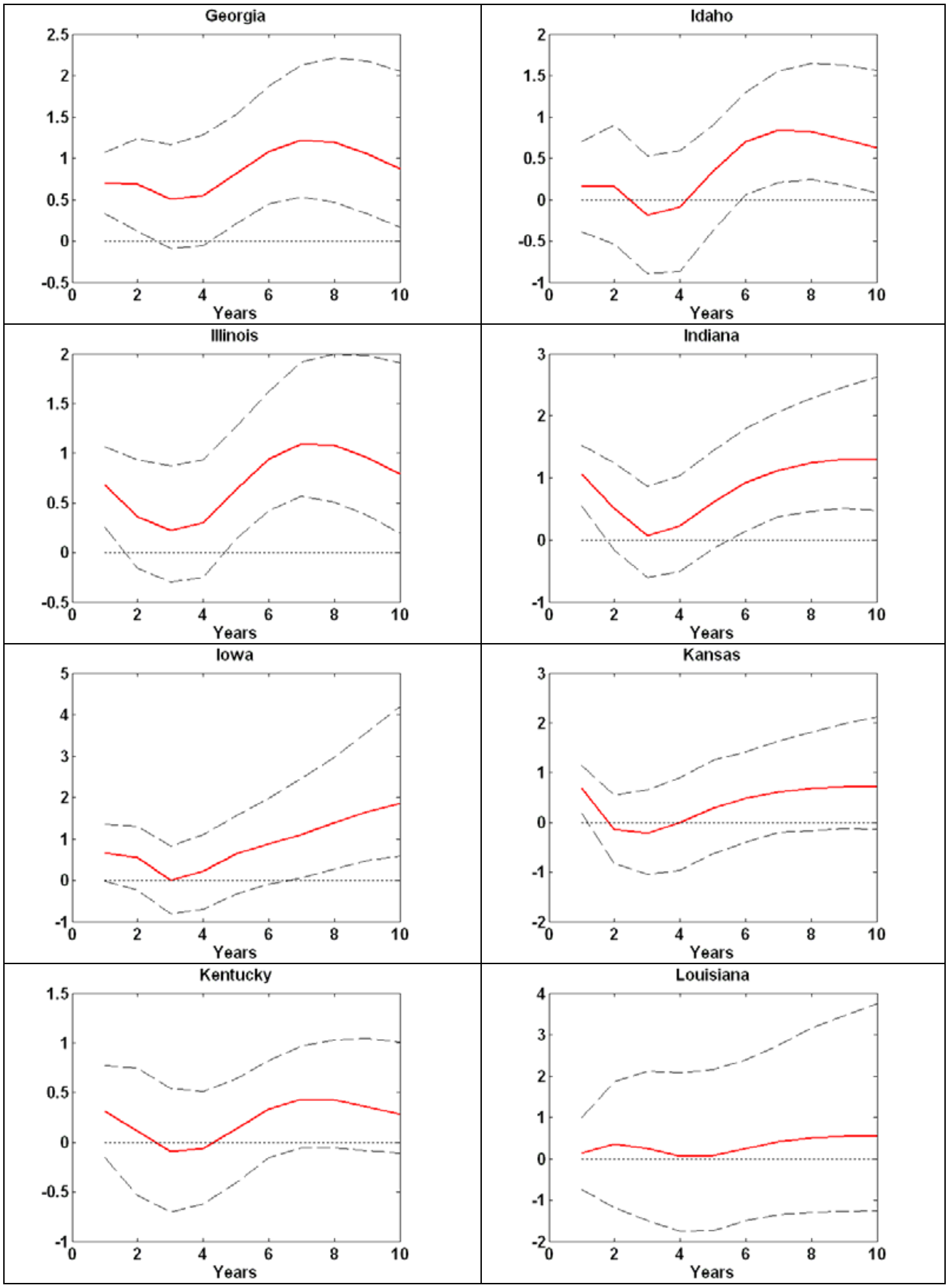
Note: The states are shaded according to the sign of the labor productivity response function: White indicates a positive response and dark grey indicates a negative response. Time Series: 1963-2005.

Figure I-7 (Continued): Productivity Responses to an Aggregate Patent Shock



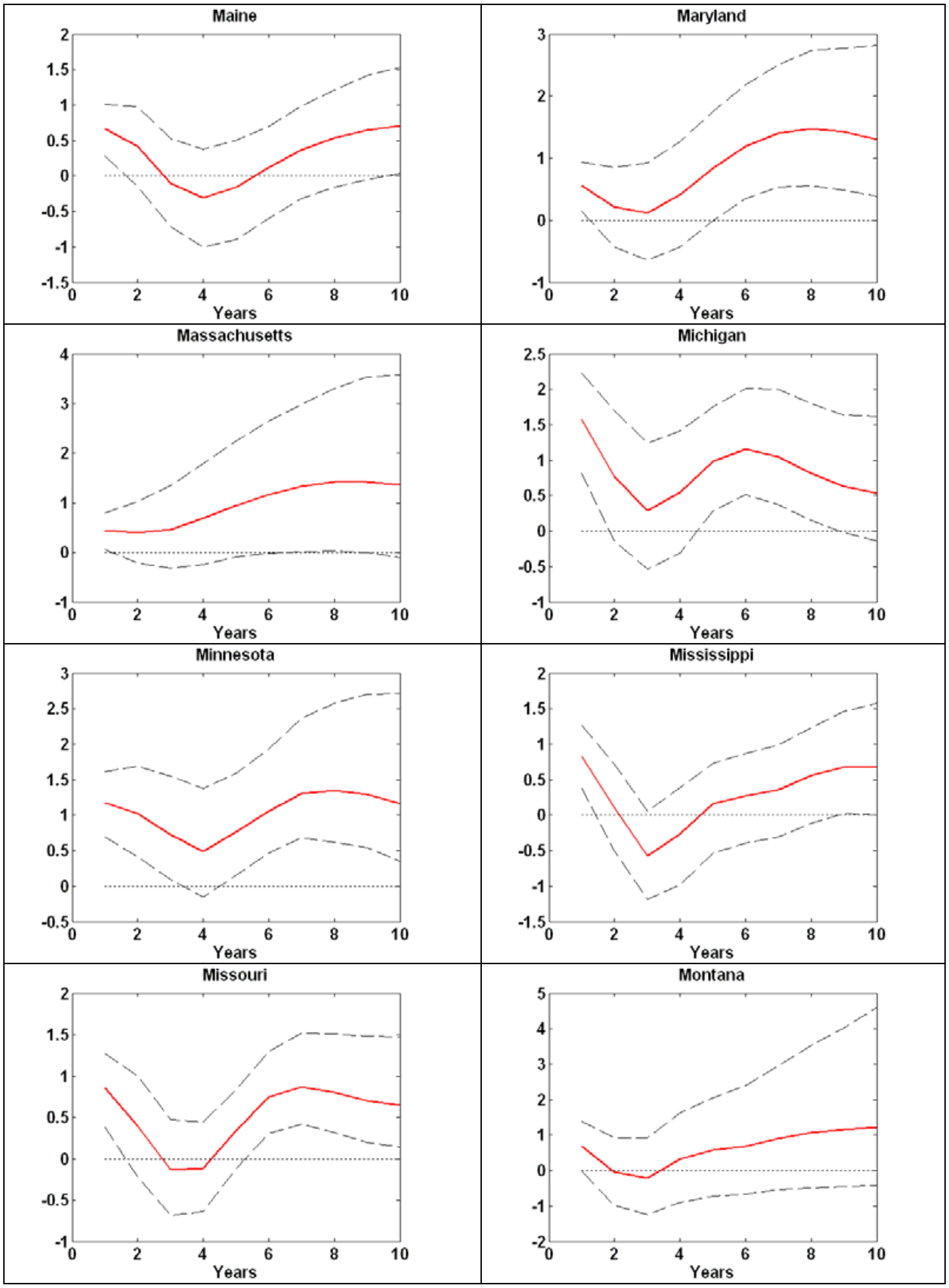
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2004.

Figure I-8: Productivity Responses to an R&D shock, 1963-2004



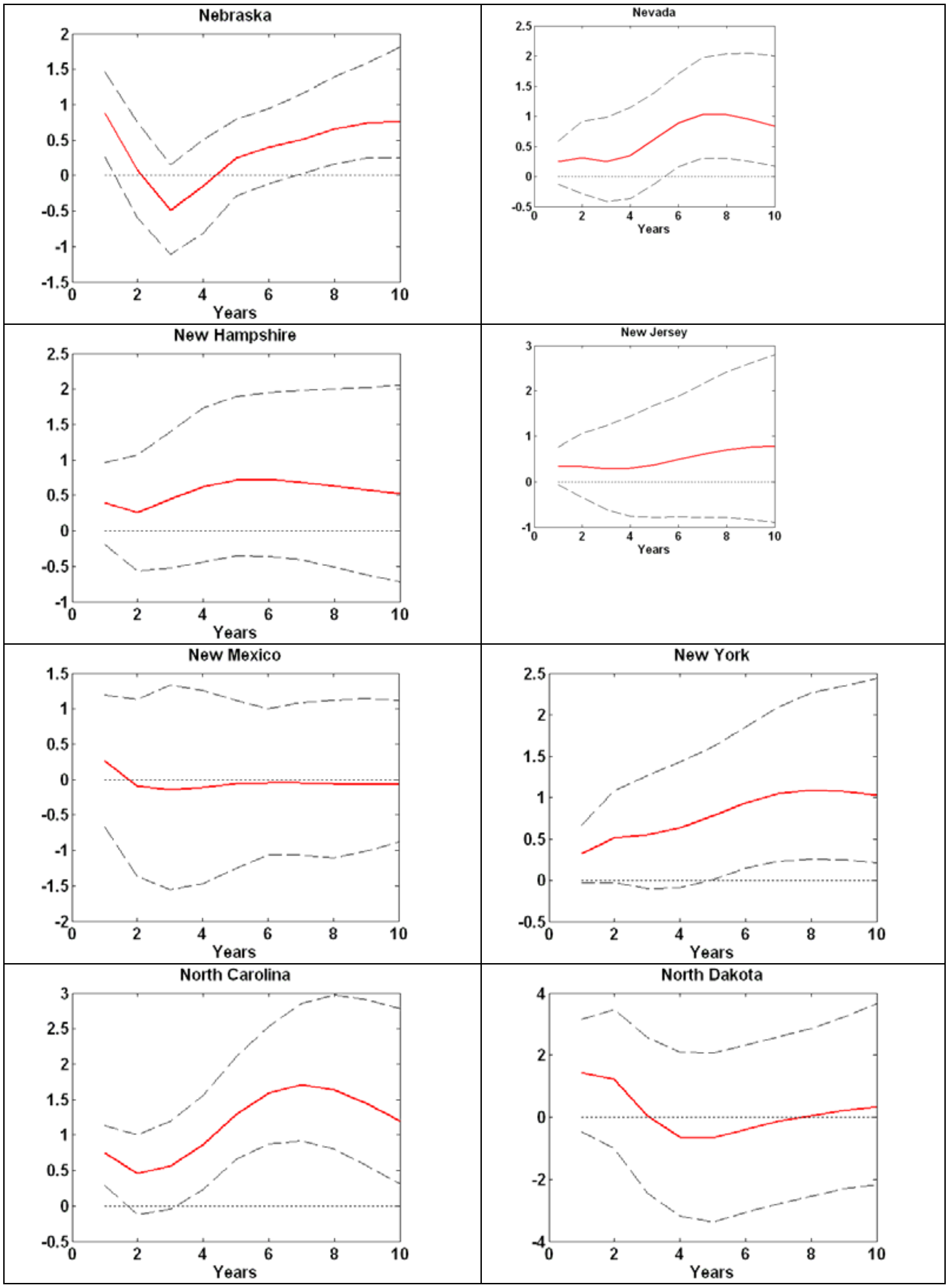
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2004.

Figure I-8 (Continued): Productivity Responses to an R&D shock, 1963-2004



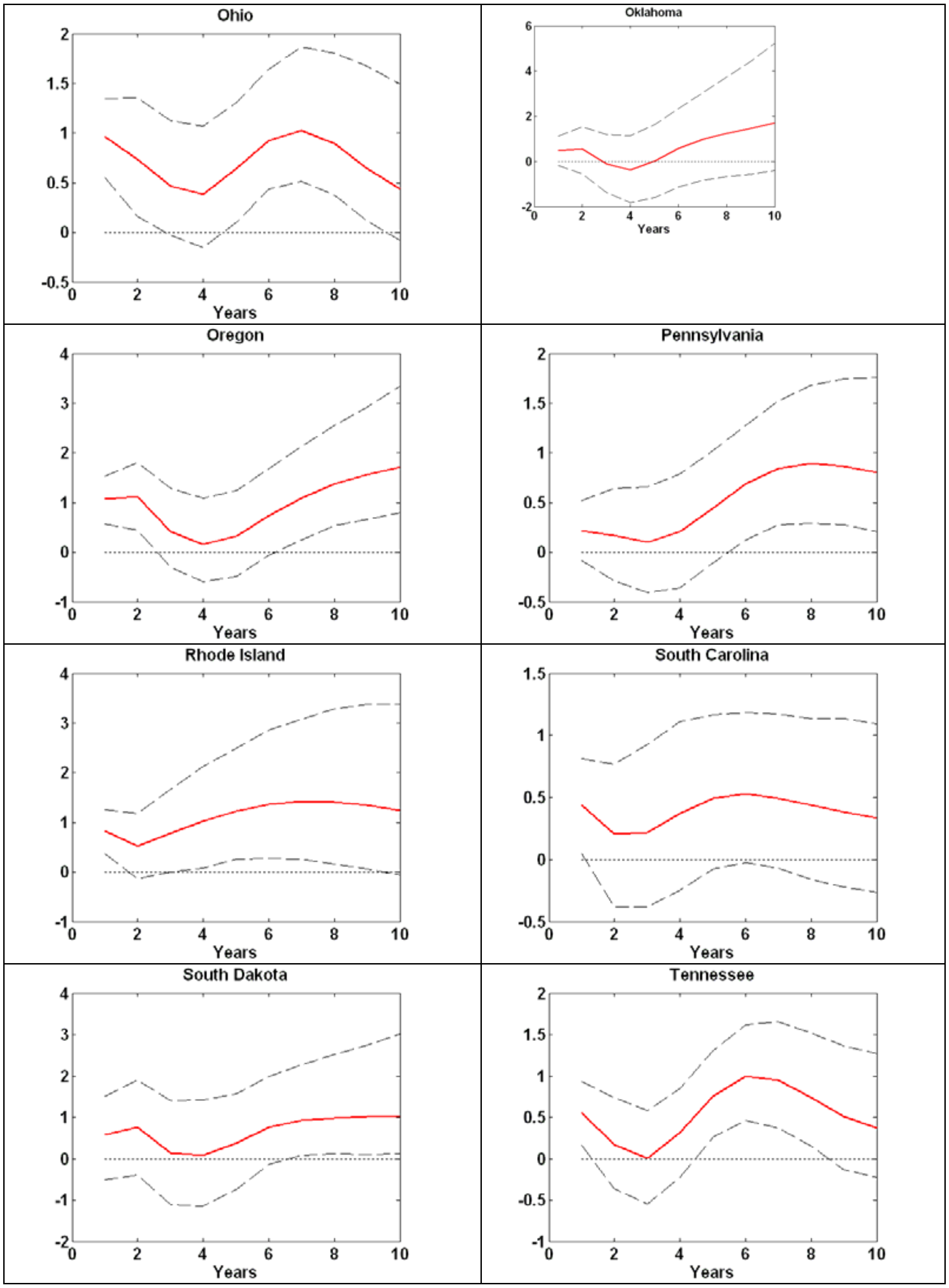
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2004.

Figure I-8 (Continued): Productivity Responses to an R&D shock, 1963-2004



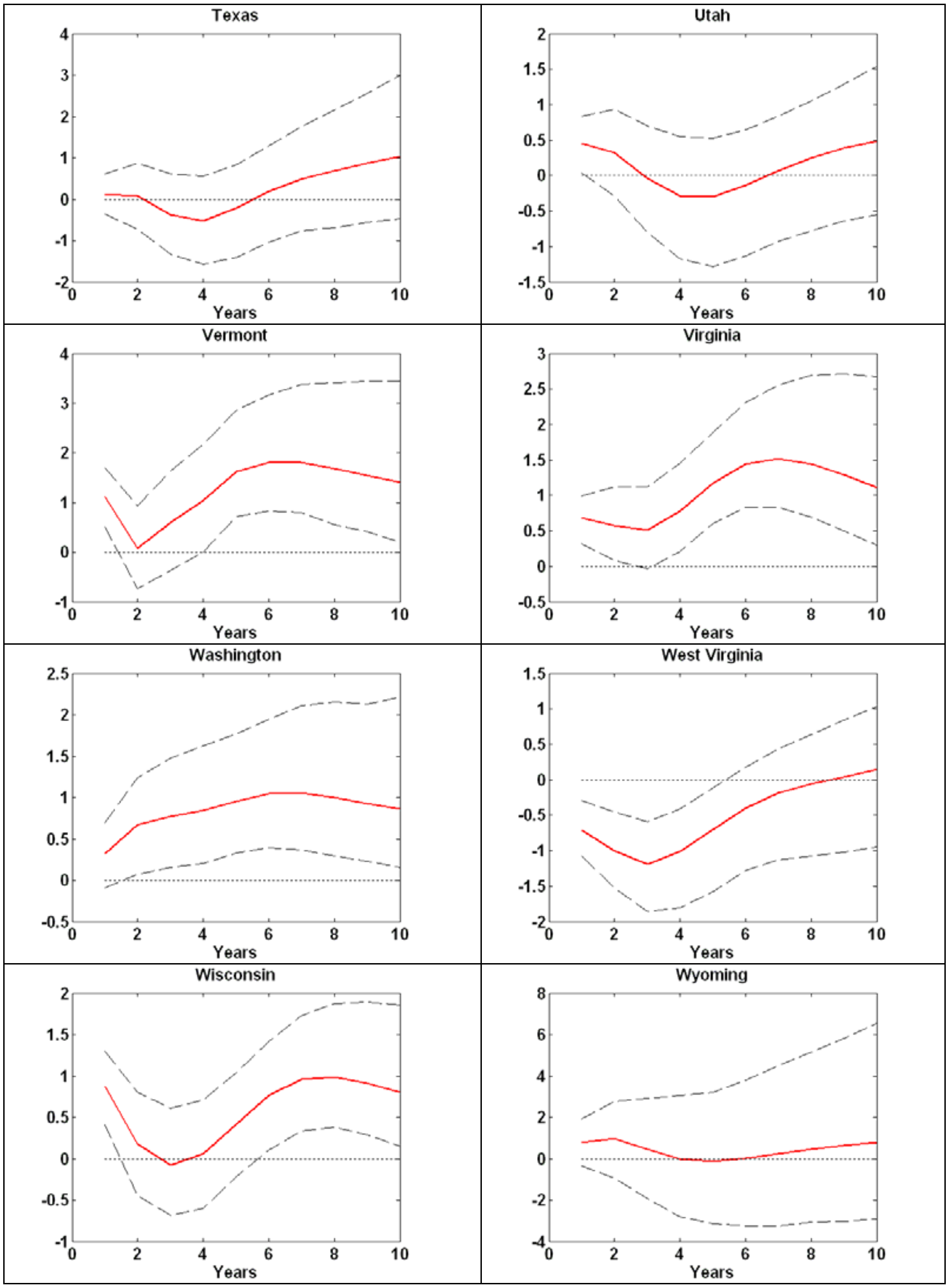
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2004.

Figure I-8 (Continued): Productivity Responses to an R&D shock, 1963-2004



Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2004.

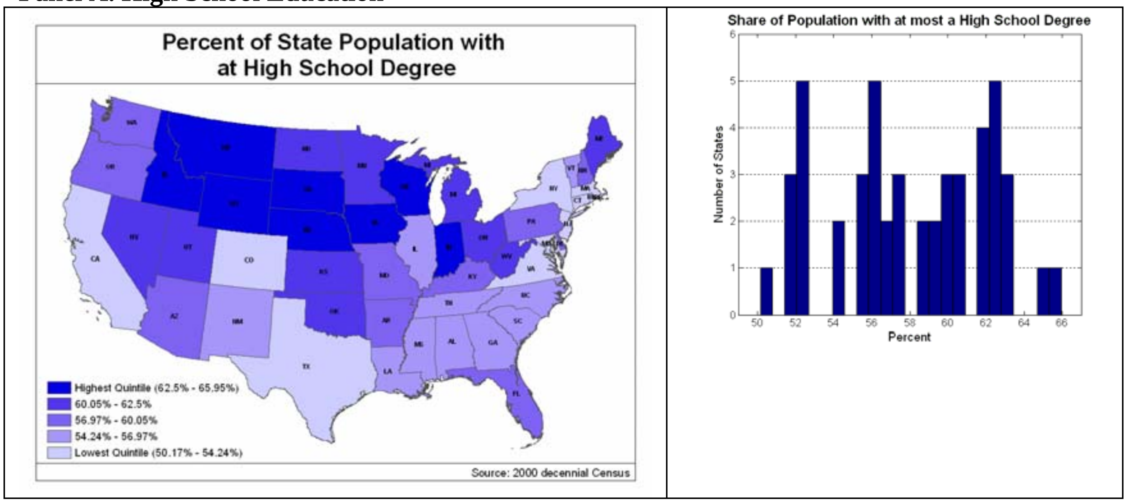
Figure I-8 (Continued): Productivity Responses to an R&D shock, 1963-2004



Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-2004.

Figure I-8 (Continued): Productivity Responses to an R&D shock, 1963-2004

Panel A. High School Education



Panel B. College Education

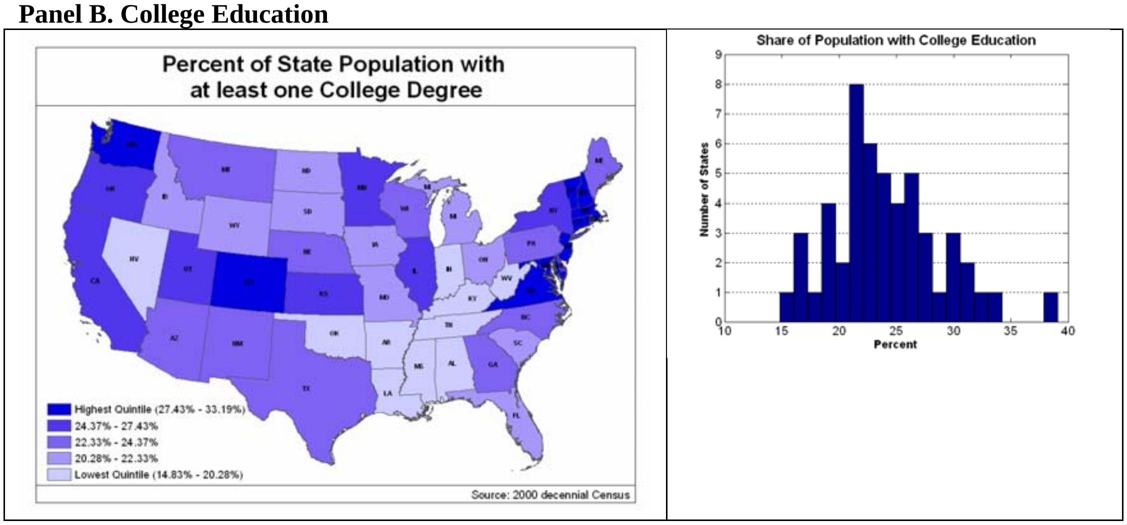
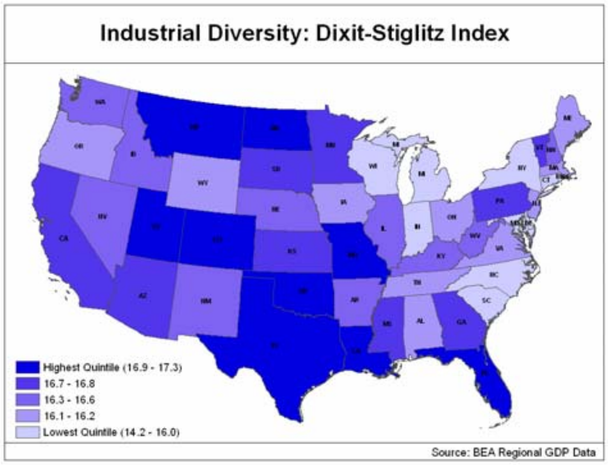
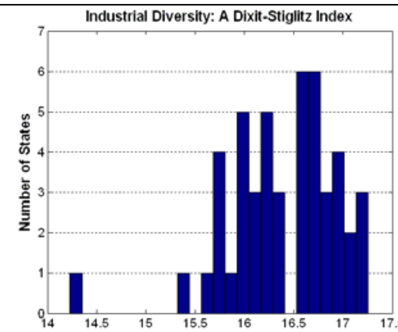


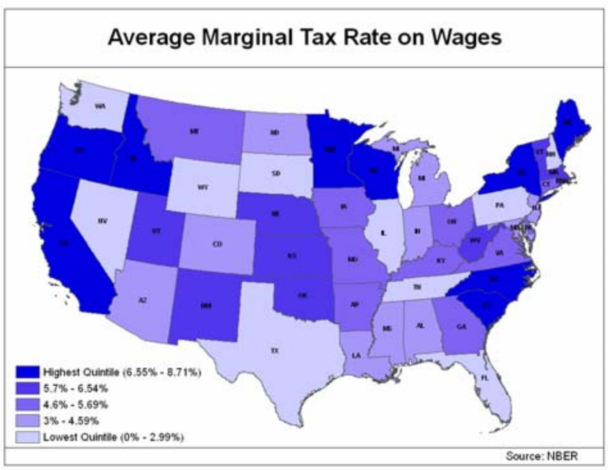
Figure I-9: State Economic Factors: Histograms and Quintile Maps

Panel C. Industrial Diversity





Panel D. Marginal Tax Rate on Wages



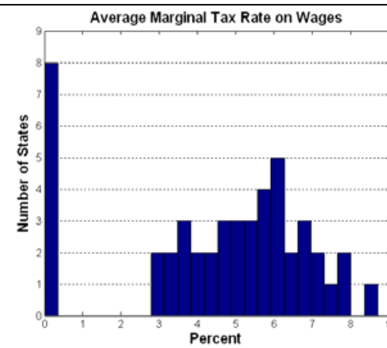
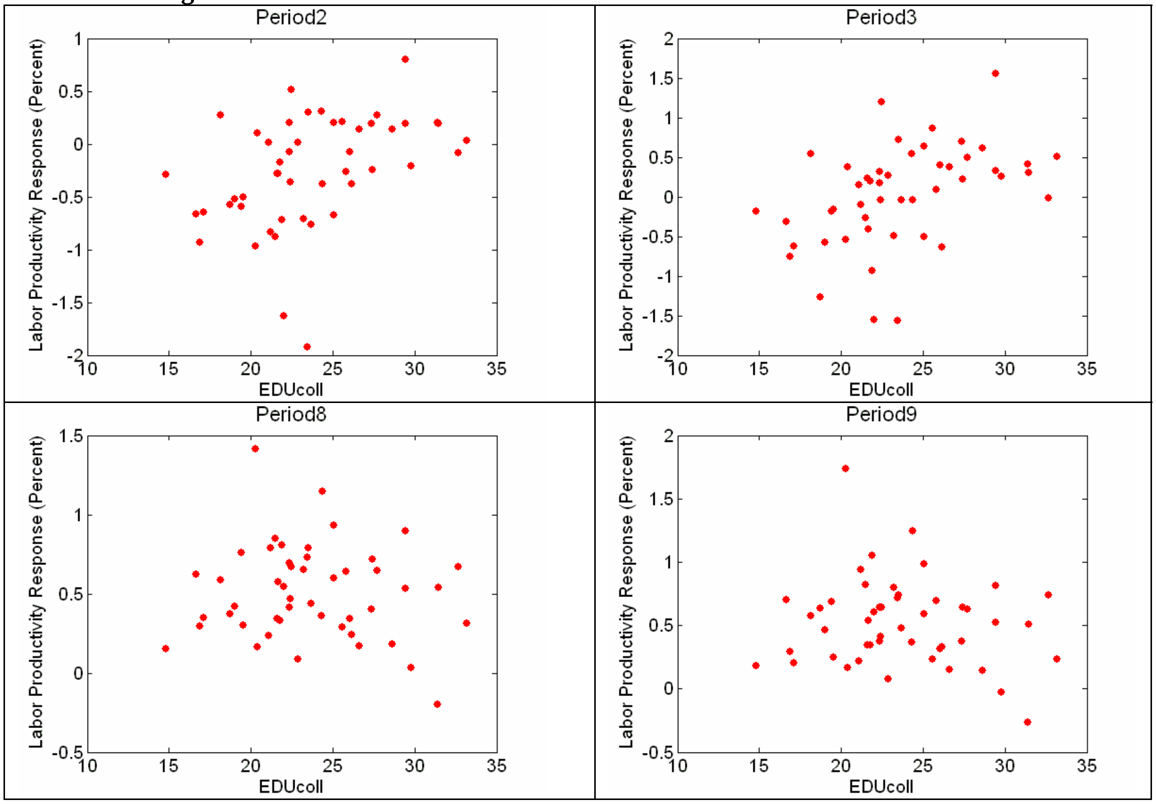


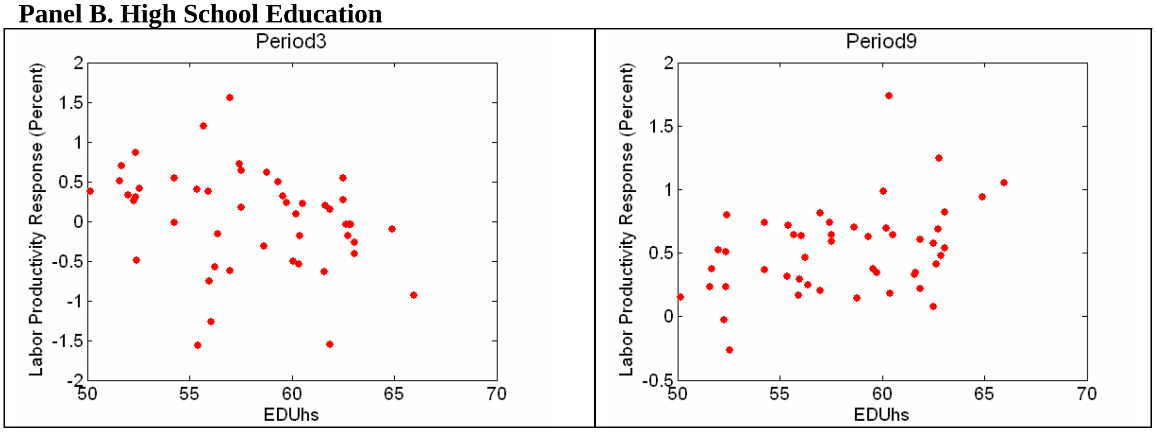
Figure I-9 (Continued): State Economic Factors: Histograms and Quintile Maps

Panel A. College Education



Note: These figures display the linearity between the share of college educated individuals in the state population and the response of labor productivity to an aggregate patent shock at horizon 2, 3, 8 and 9, respectively. EDUcoll is based on year 2000 values.

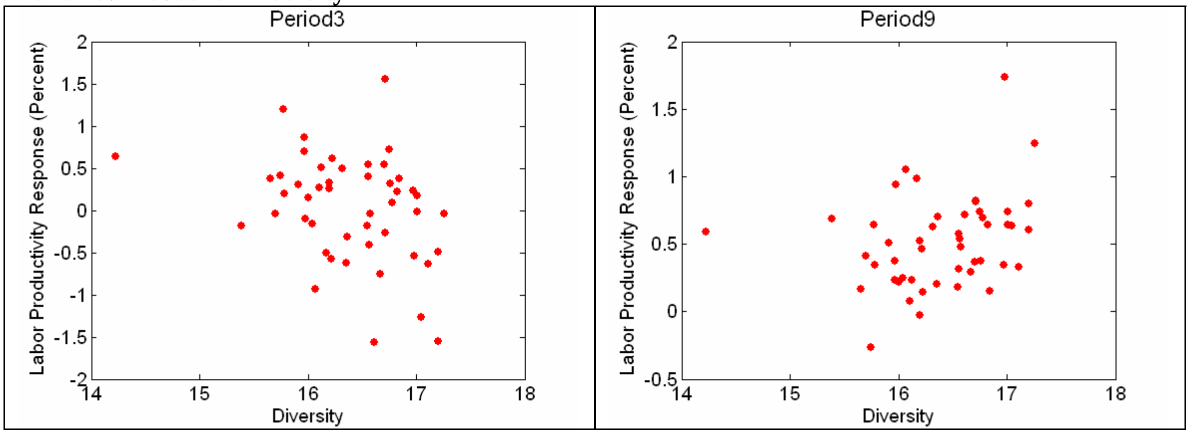
Panel B. High School Education



Note: These figures display the linearity between the share of high school educated individuals in the state population and the response of labor productivity to an aggregate patent shock at horizon 3 and 9, respectively. EDUhs is based on year 2000 values.

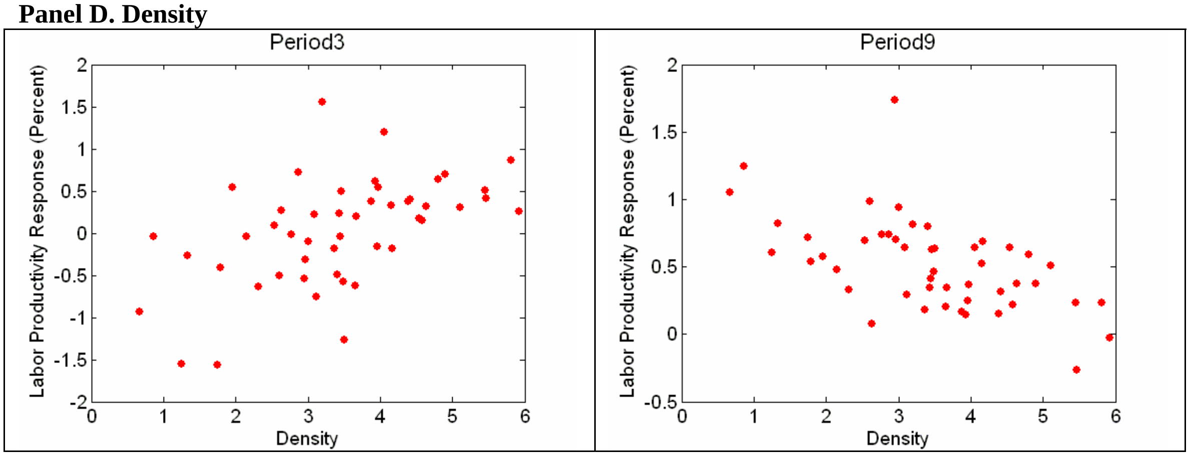
Figure I-10: Scatter Plots: Benchmark Productivity Responses vs. State-level Economic Factors

Panel C. Industrial Diversity



Note: These figures display the linearity between industrial diversity variable and the response of labor productivity to an aggregate patent shock at horizon 3and 9, respectively. Diversity is based on year 2000 values.

Panel D. Density



Note: These figures display the linearity between the density of the state population and the response of labor productivity to an aggregate patent shock at horizon 3 and 9, respectively. Density is based on year 2000 values.

Figure I-10 (Continued): Scatter Plots: Benchmark Productivity Responses vs. State-level Economic Factors

I.I. Appendix

I.I.1 Data

I.I.1.1 Time series Data

Labor Productivity:

- Gross Domestic Product by State (GDPS) is from the Bureau of Economic Analysis (BEA)
- State non-farm employment is from the Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) Annual Observations.
- The productivity data are spliced in 1997 by multiplying the post-1997 data with the ratio of 1997 SIC value to the 1997 NAICS value.

Patent Data:

- Total annual utility patent applications in the U.S. from the United States Patent and Trademark Office (USPTO).
- NBER Patent Data File contains applications that eventually were granted. See Hall, Jaffe, and Trajtenberg (2001) for details on the data.

R&D Data:

- BEA Research and Development Satellite Account. Real values are available from 1959 to 2004. See Robbins and Moylan (2007).

Manufacturing Employment Data:

- BEA state-level manufacturing employment and total BEA state-level employment. The data are available from 1969-2005.

State-Level Wage and Salary Disbursements:

- BEA State and Local Area Personal Income Data.

Fuel PPI Relative to the PPI:

- BLS Producer Price Index.

Consumer Price Index:

- BLS Inflation and Consumer Spending.

Gross Domestic Product Deflator:

- BEA National Income and Product Accounts.

I.I.1.2 Cross-Sectional Data

Education High School (EDUhs)

- Decennial Census data that contains the share of the population over the age of 25 with at least a high school education but not a college degree

Education College (EDUcoll)

- Decennial Census data that contains the share of the population over the age of 25 with at least a college education

Education Combined (EDUalhs)

- Decennial Census data that contains the share of the population over the age of 25 with at least a high school education

Education Spending per Student (EDUSpend)

- The data are from the National Public Education Financial Survey run by the National Center for Education Statistics.

Industrial Diversity (Diversity)

- Dixit-Stiglitz Index of BEA GDP by state data at the two digit industrial level.
- 20 industries are used for the NAICS data

Average Establishment Size (Establishment Size)

- Establishment size distribution from the Census County Business Pattern data.

Union Membership (Union)

- This data represent the percentage of each state's nonagricultural wage and salary employees who are union members. Estimates are based on the 1983-2006 Current Population Survey (CPS) Outgoing Rotation Group (ORG) earnings files, the 1973-81 May CPS earnings files, and the BLS publication *Directory of National Unions and Employee Associations*, various years. Details on data and methodology are provided in Hirsch, MacPherson, and Vroman (2001).

Manufacturing (Manufact)

- Share of BEA State GDP associated with the manufacturing sector.
- Nominal State Manufacturing GDP divided by Nominal State GDP.

Density

- BEA population estimates divided by the area of each state in square kilometers.

Income Tax

- NBER estimates of average marginal state income tax rate on wages using a nationally representative sample from 1995.

Corporate Tax

- Corporate income tax rates reported by the Tax Foundation (www.taxfoundation.org).
- This variable contains the highest marginal tax rate.

Property Tax per Person

- These estimates are from the Tax Foundation (www.taxfoundation.org) who use Census information to aggregate county level property tax data to the state level and then calculate the average property tax paid by a state resident.

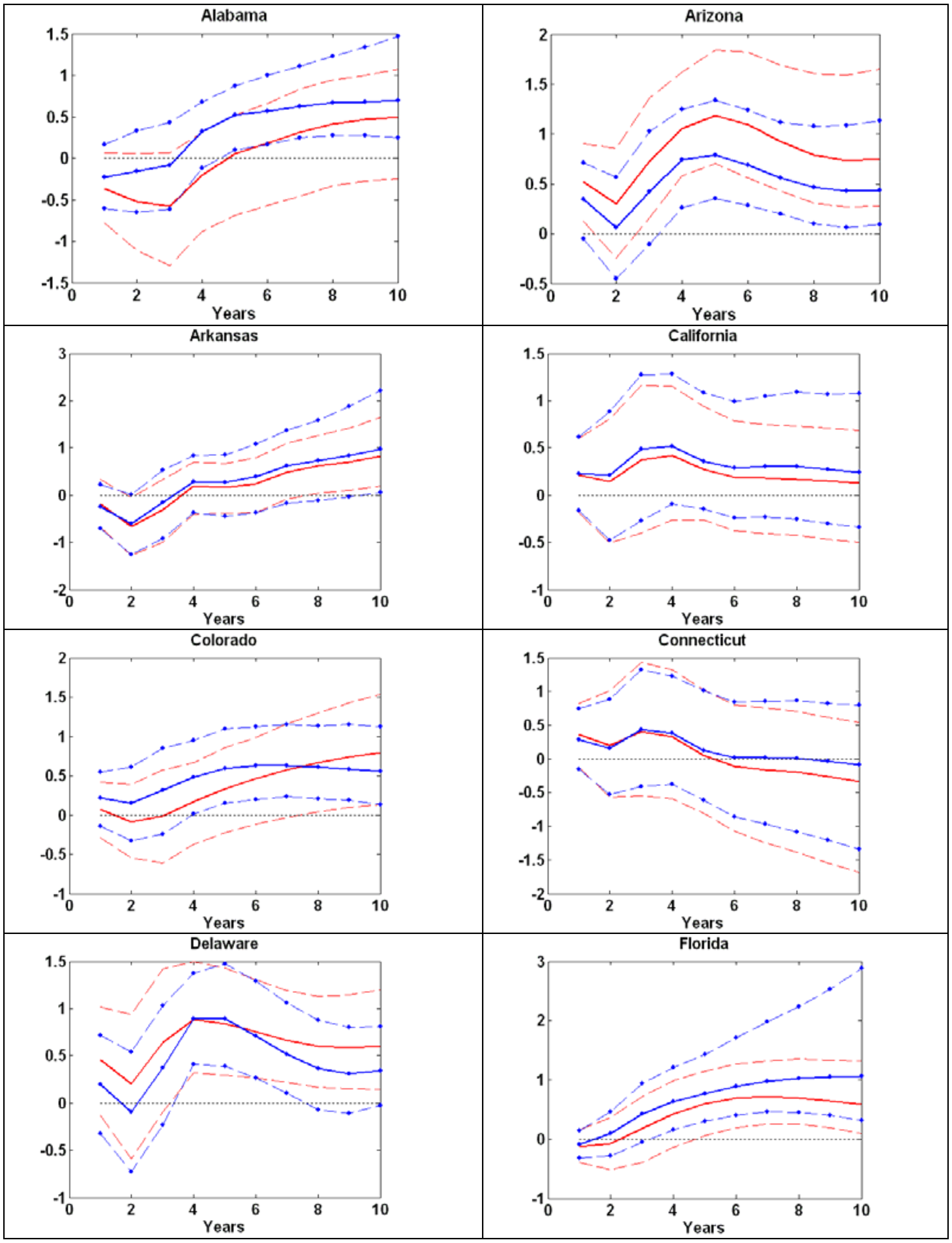
State Minimum Wage

- BLS data on the maximum between the state minimum wage and the federally mandated minimum wage.

Median Age

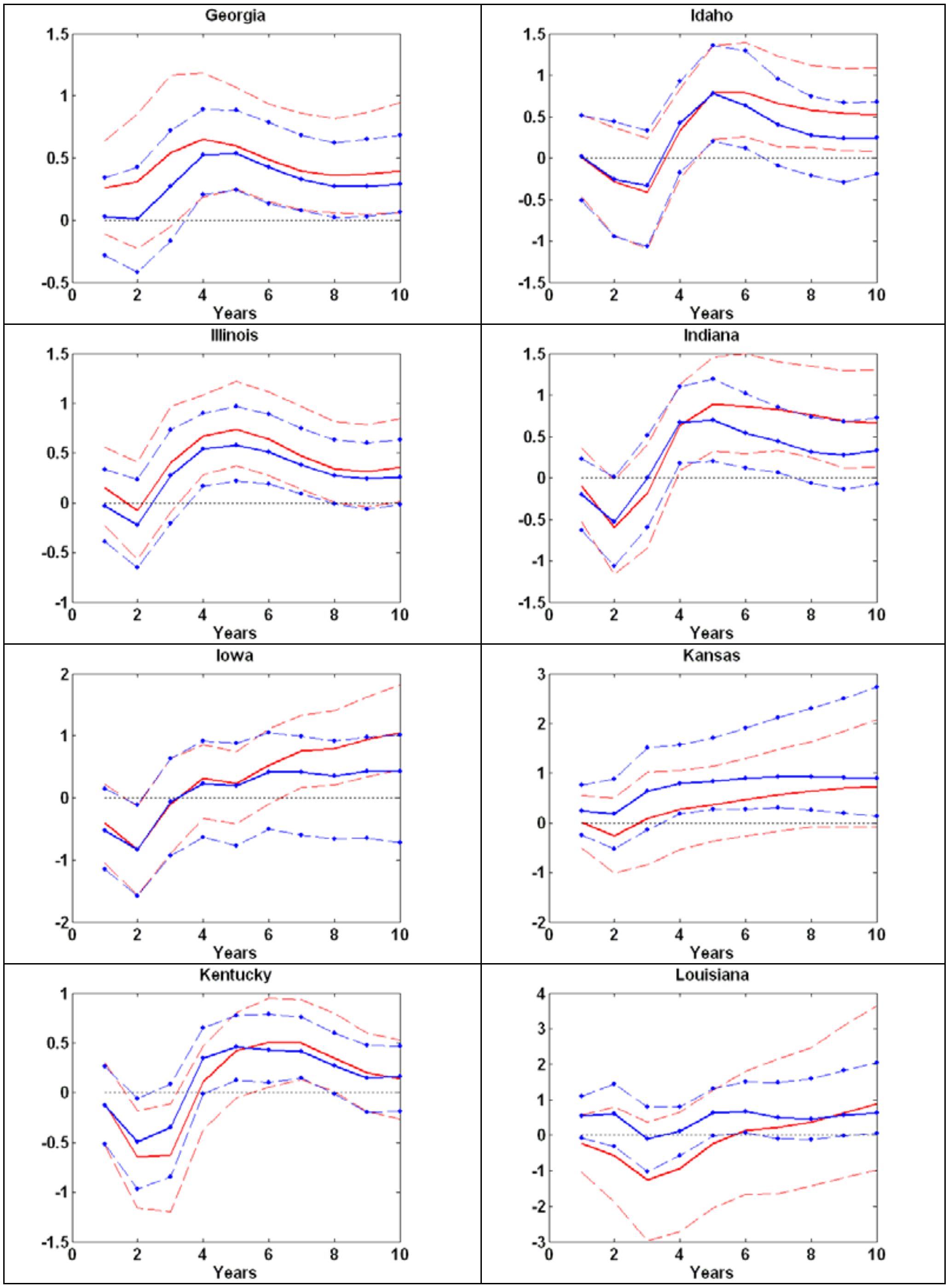
- The median age within a state is gathered from the decennial Census age distribution data from the American Fact Finder.

I.I.2 Additional Figures



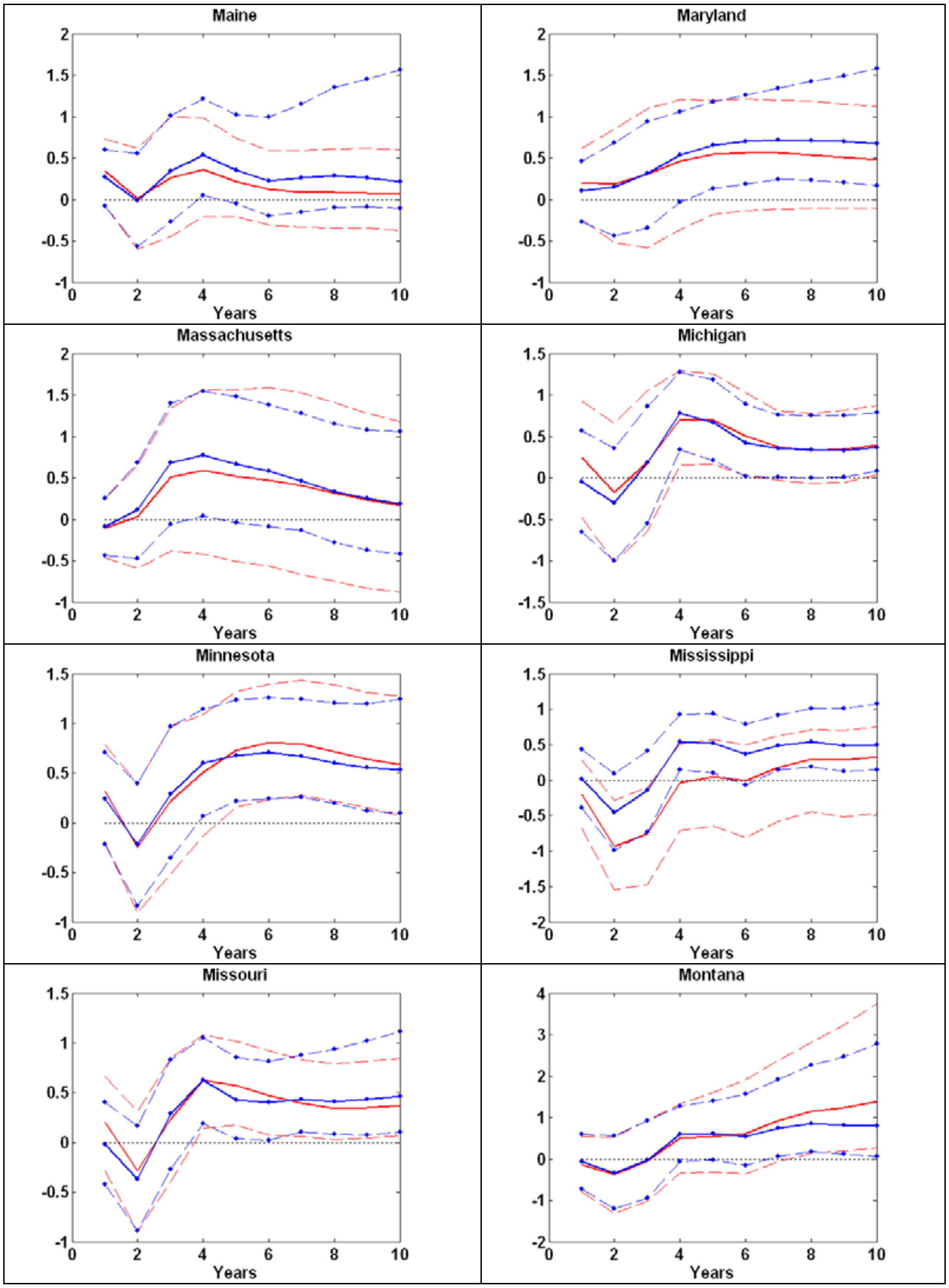
Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are the response functions that condition on the relative price of fuel. The dotted lines are 90% confidence bands. The Y-axis is in percent. Time Series: 1963-2005.

Figure I-11: Comparing Responses of Productivity to a Patent shock: With and Without Conditioning on the Relative FuelPPI.



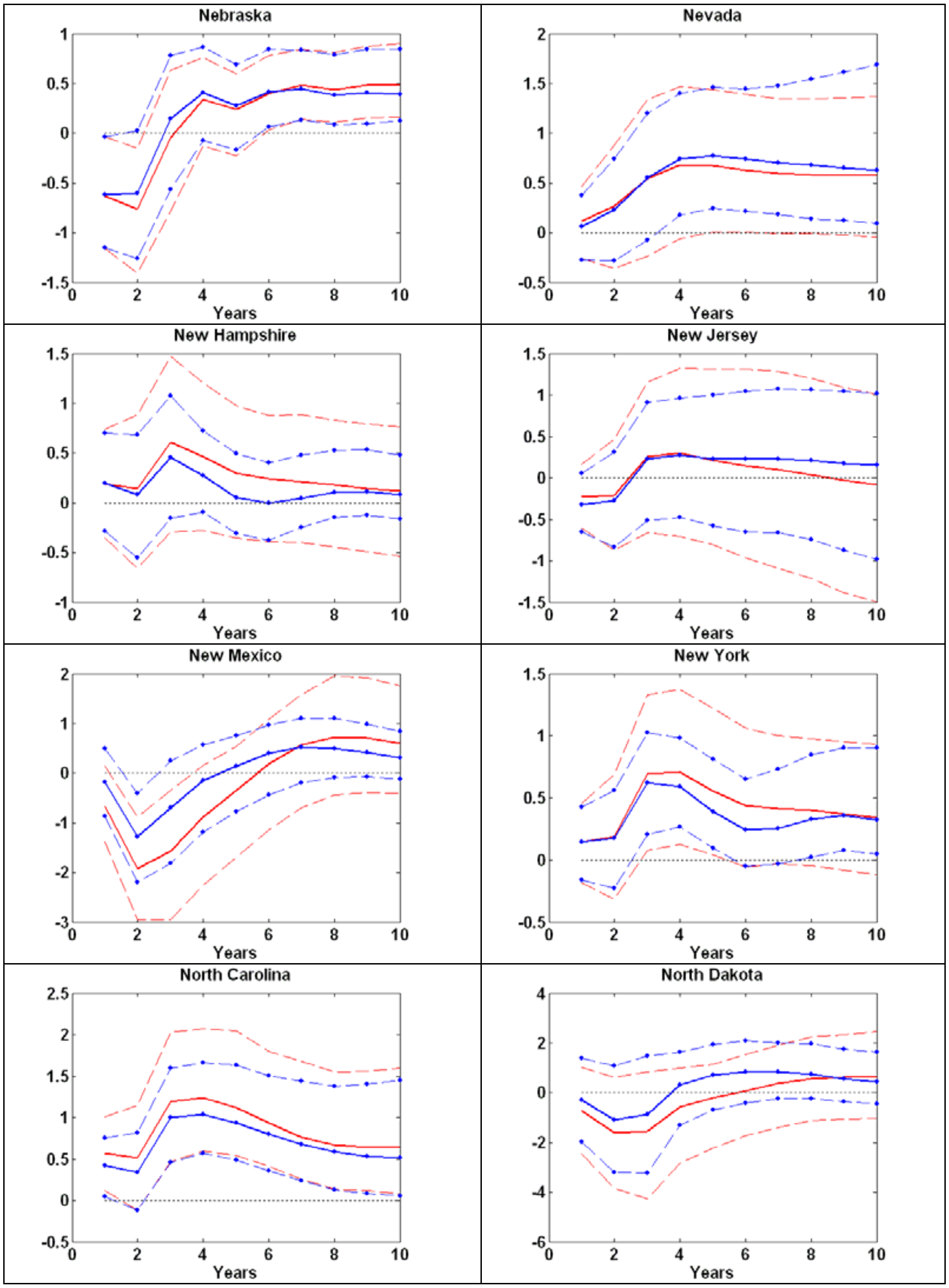
Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are the response functions that condition on the relative price of fuel. The dotted lines are 90% confidence bands. The Y-axis is in percent. Time Series: 1963-2005.

Figure I-11 (Continued): Comparing Responses of Productivity to a Patent shock: With and Without Conditioning on the Relative FuelPPI



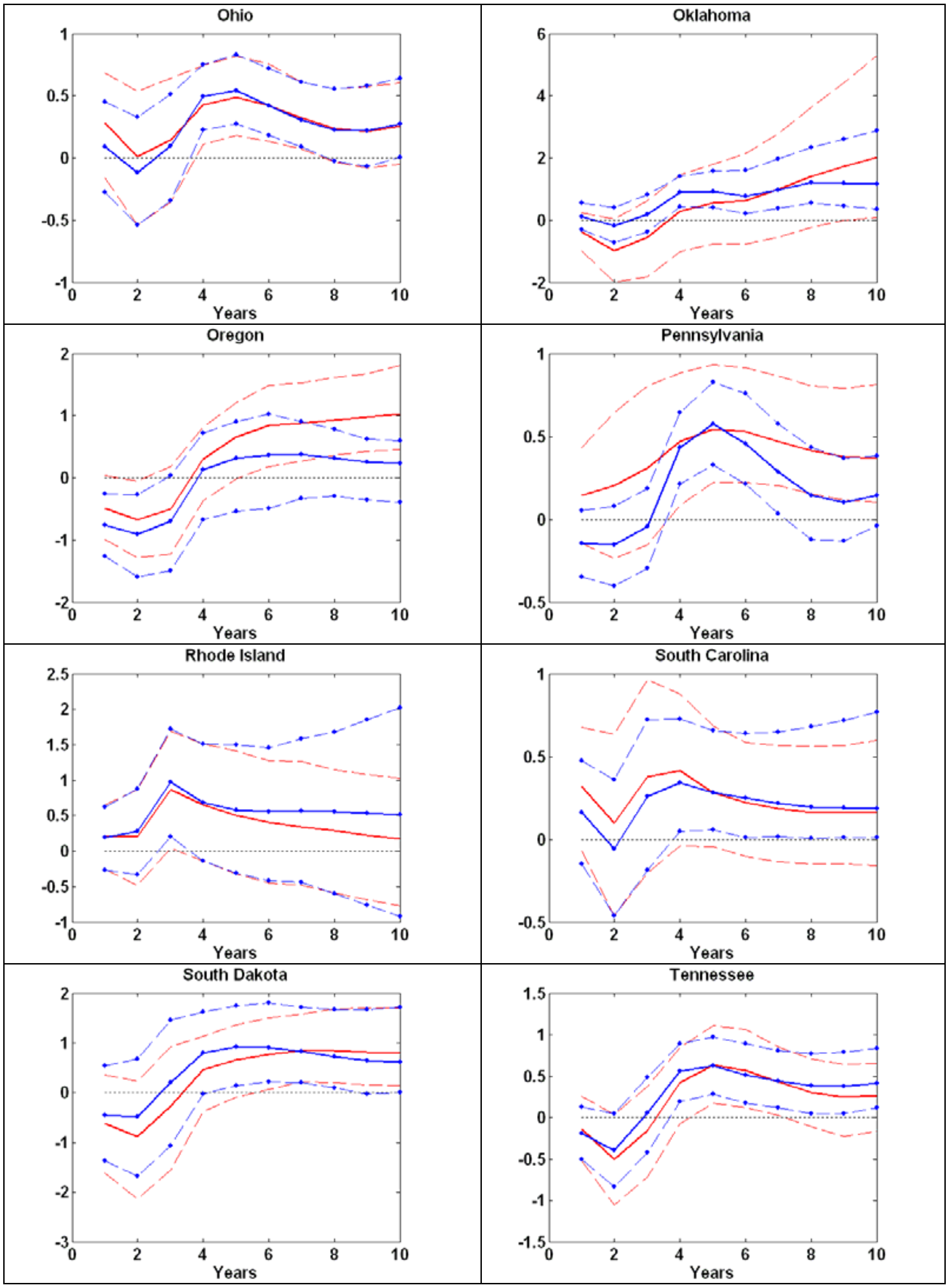
Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are the response functions that condition on the relative price of fuel. The dotted lines are 90% confidence bands. The Y-axis is in percent. Time Series: 1963-2005.

Figure I-11 (Continued): Comparing Responses of Productivity to a Patent shock: With and Without Conditioning on the Relative FuelPPI



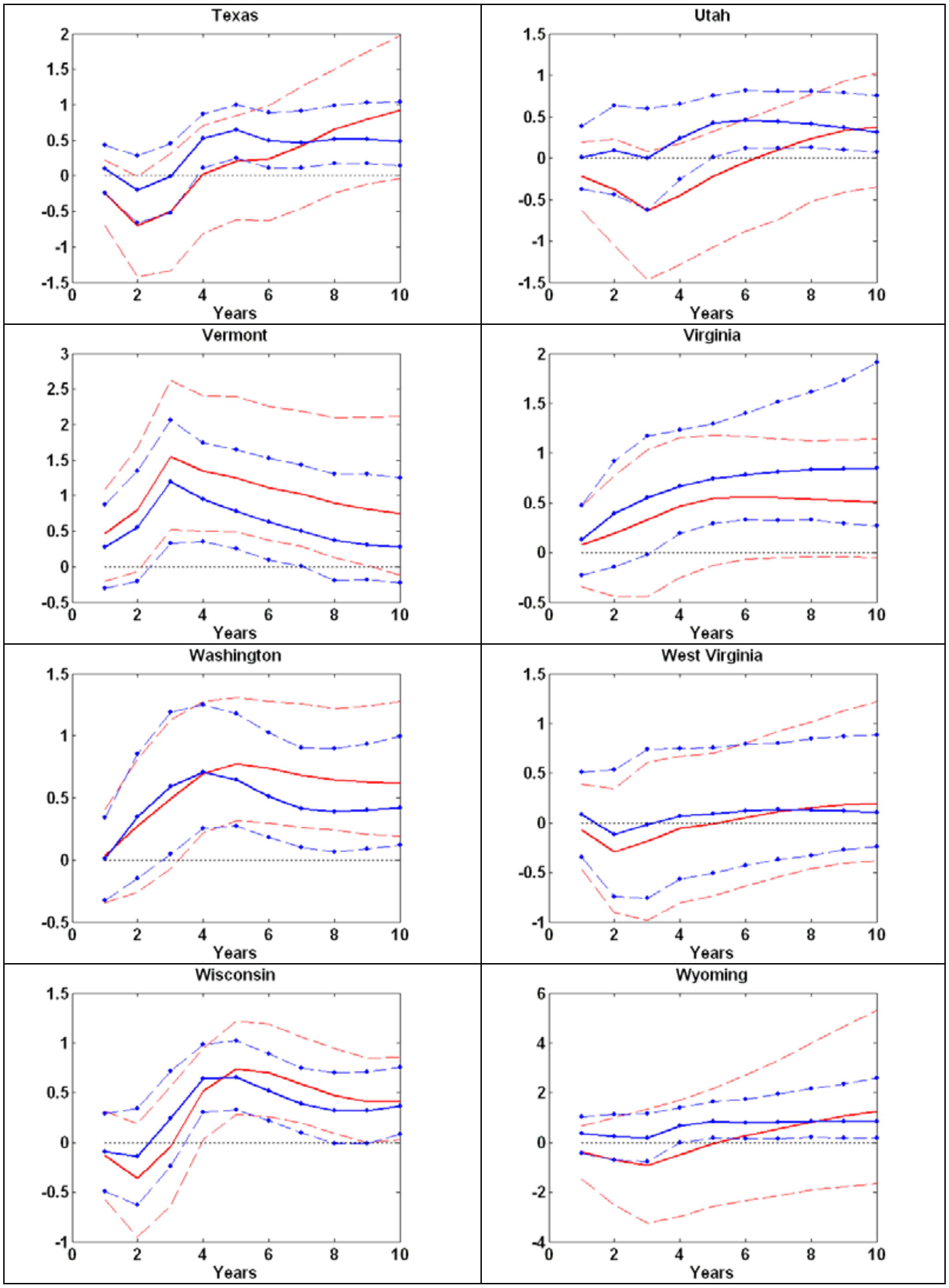
Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are the response functions that condition on the relative price of fuel. The dotted lines are 90% confidence bands. The Y-axis is in percent. Time Series: 1963-2005.

Figure I-11 (Continued): Comparing Responses of Productivity to a Patent shock: With and Without Conditioning on the Relative FuelPPI



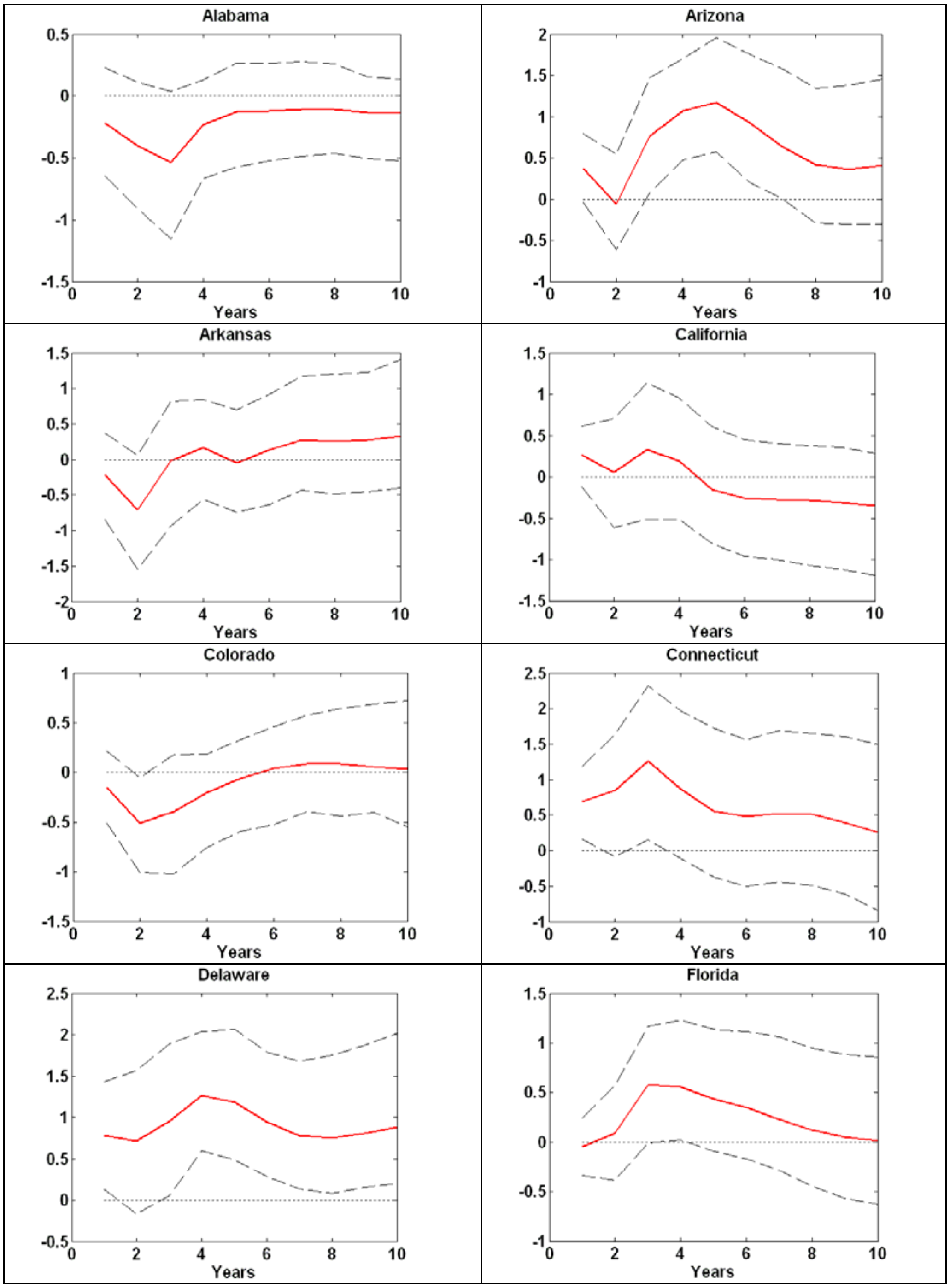
Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are the response functions that condition on the relative price of fuel. The dotted lines are 90% confidence bands. The Y-axis is in percent. Time Series: 1963-2005.

Figure I-11 (Continued): Comparing Responses of Productivity to a Patent shock: With and Without Conditioning on the Relative FuelPPI



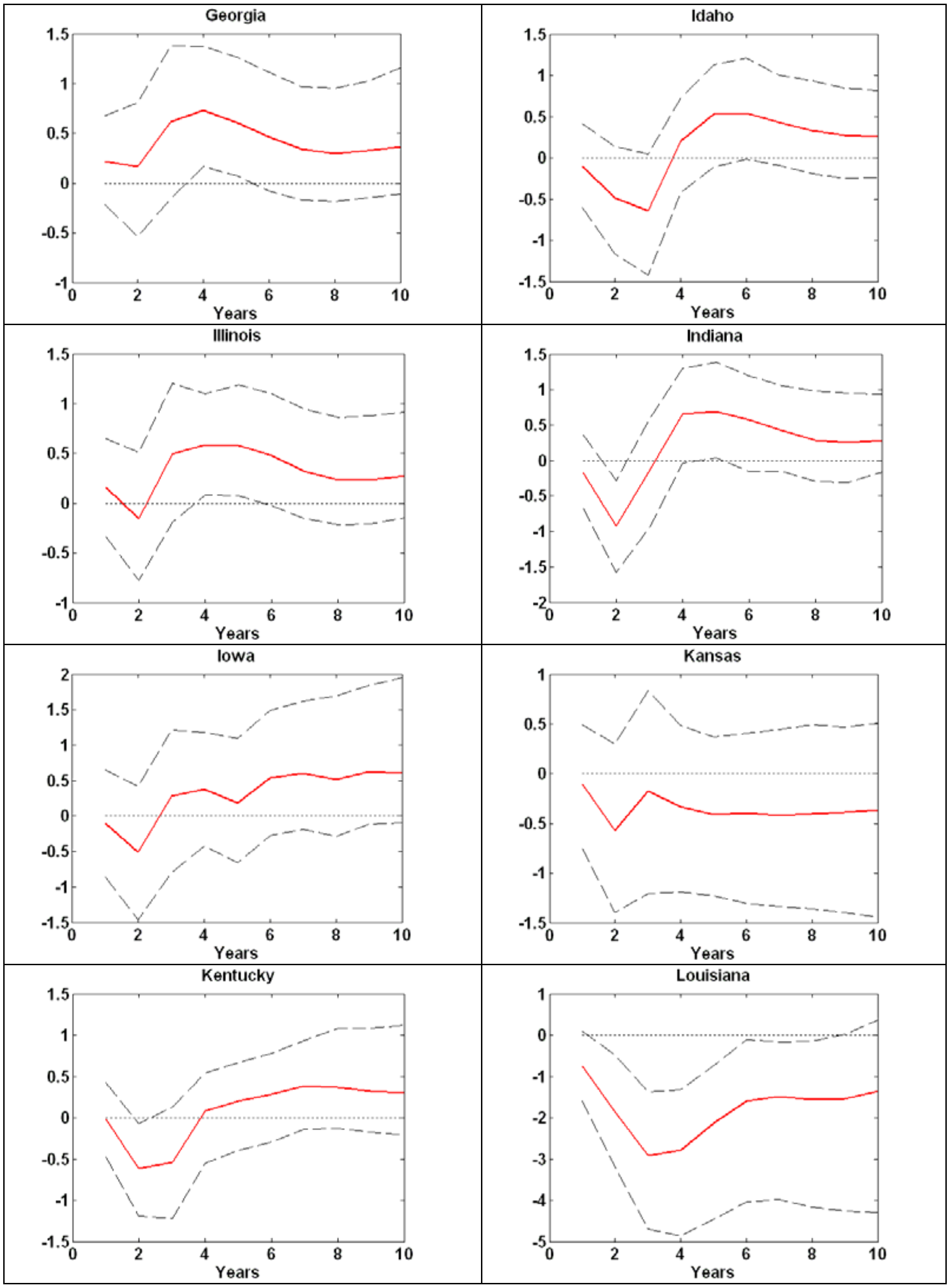
Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are the response functions that condition on the relative price of fuel. The dotted lines are 90% confidence bands. The Y-axis is in percent. Time Series: 1963-2005.

Figure I-11 (Continued): Comparing Responses of Productivity to a Patent shock: With and Without Conditioning on the Relative FuelPPI



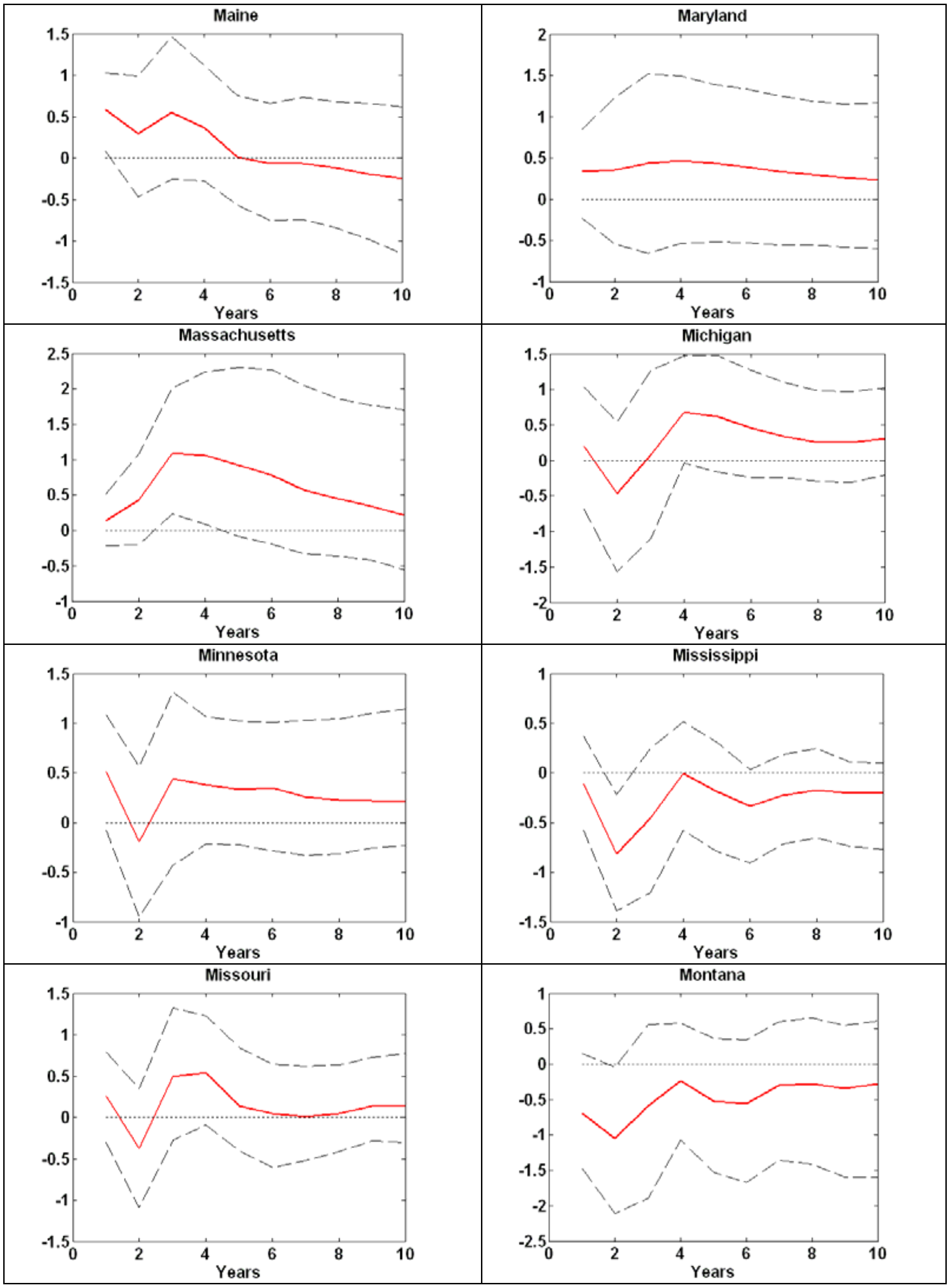
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-1997.

Figure I-12: Productivity Responses to a Patent Shock, 1963-1997



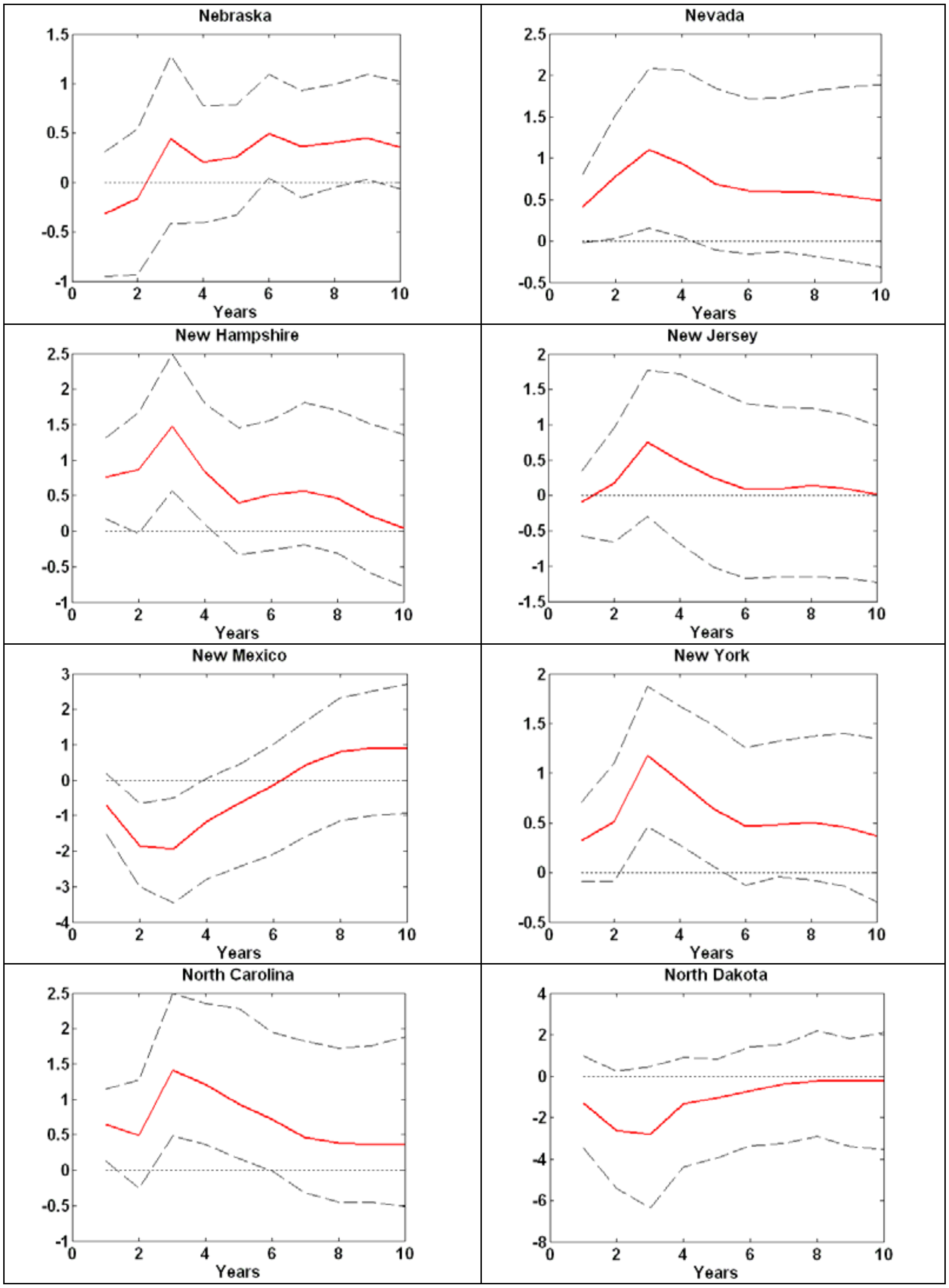
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-1997.

Figure I-12 (Continued): Productivity Responses to a Patent Shock, 1963-1997



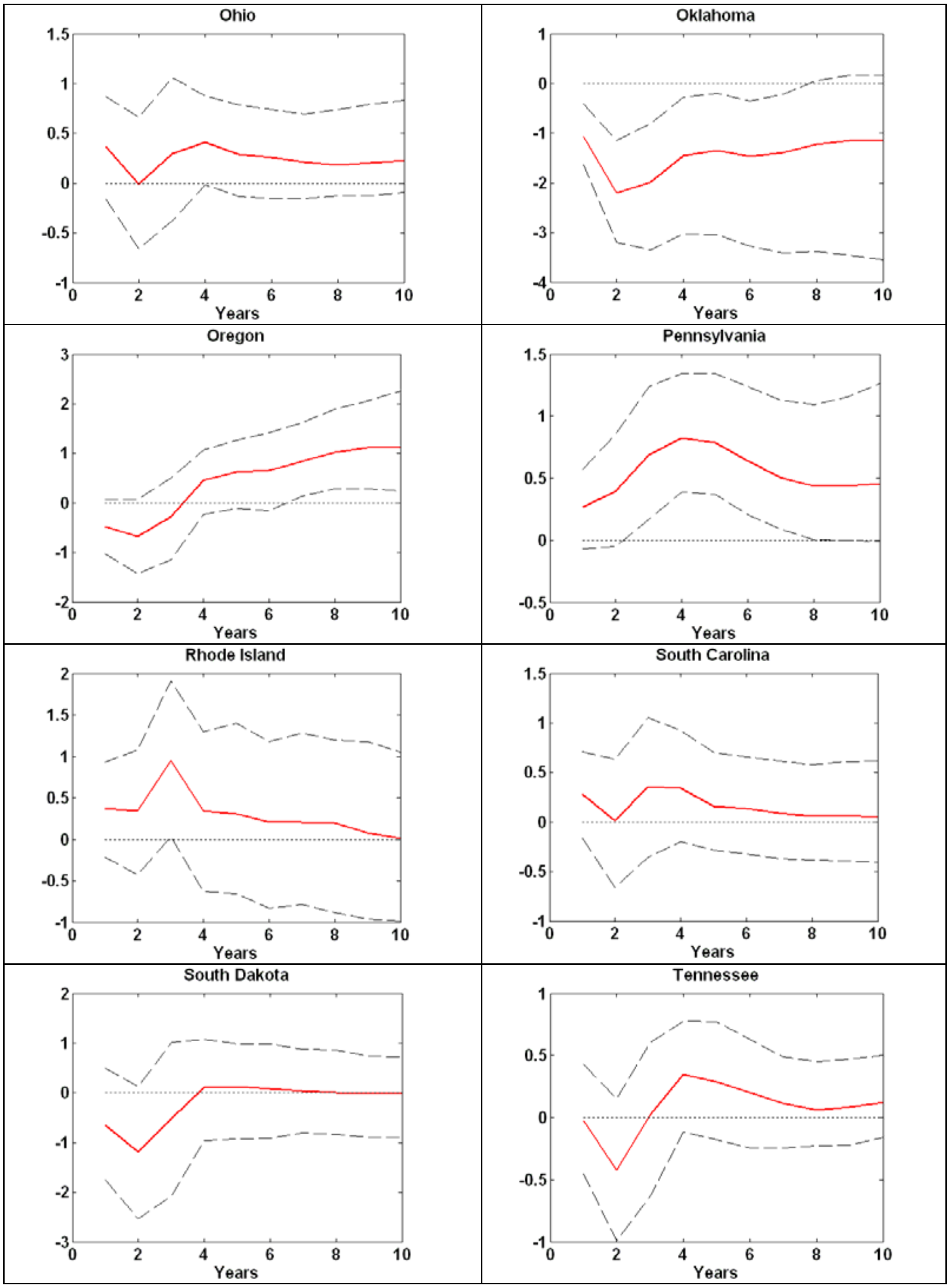
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-1997.

Figure I-12 (Continued): Productivity Responses to a Patent Shock, 1963-1997



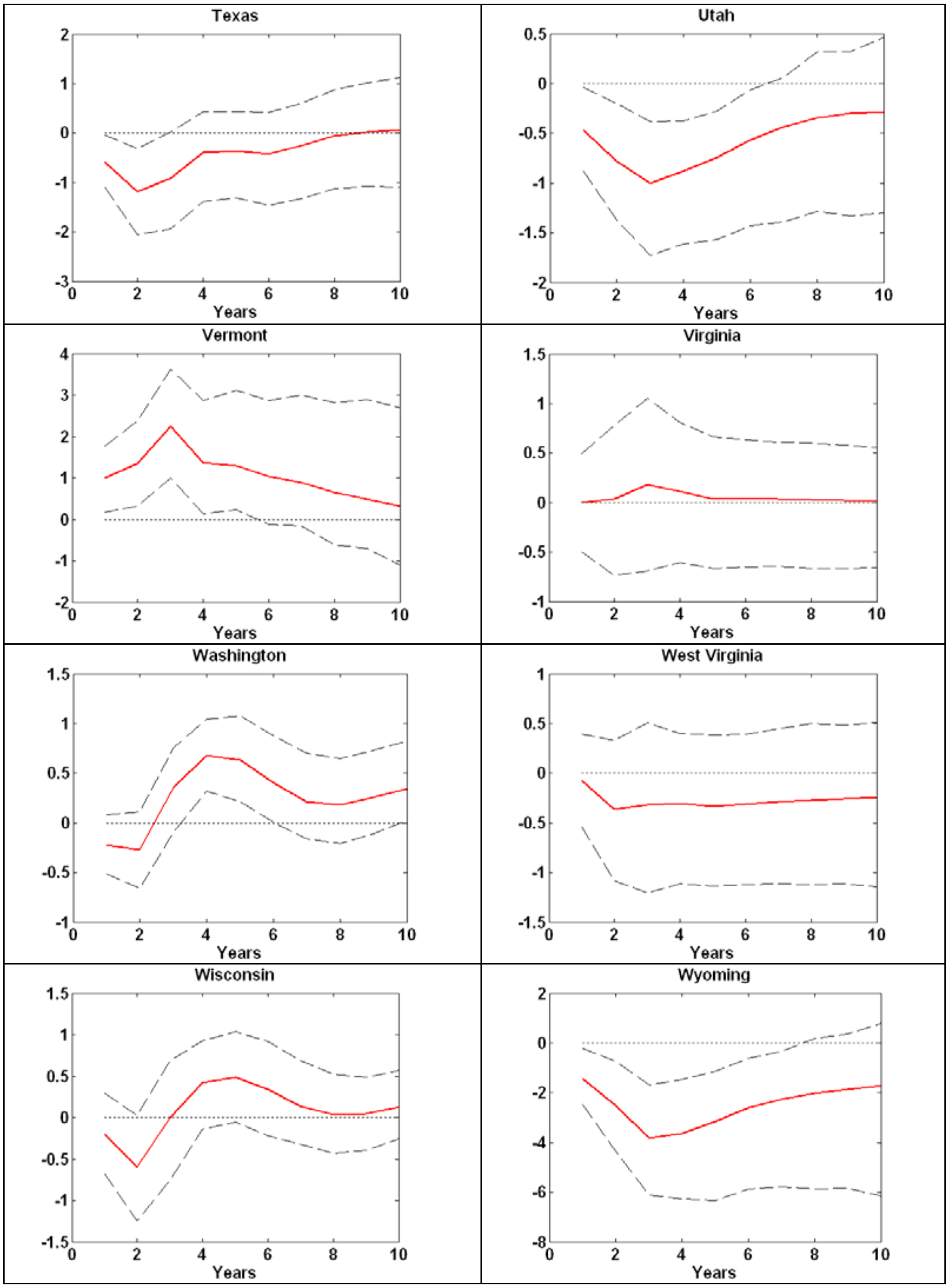
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-1997.

Figure I-12 (Continued): Productivity Responses to a Patent Shock, 1963-1997



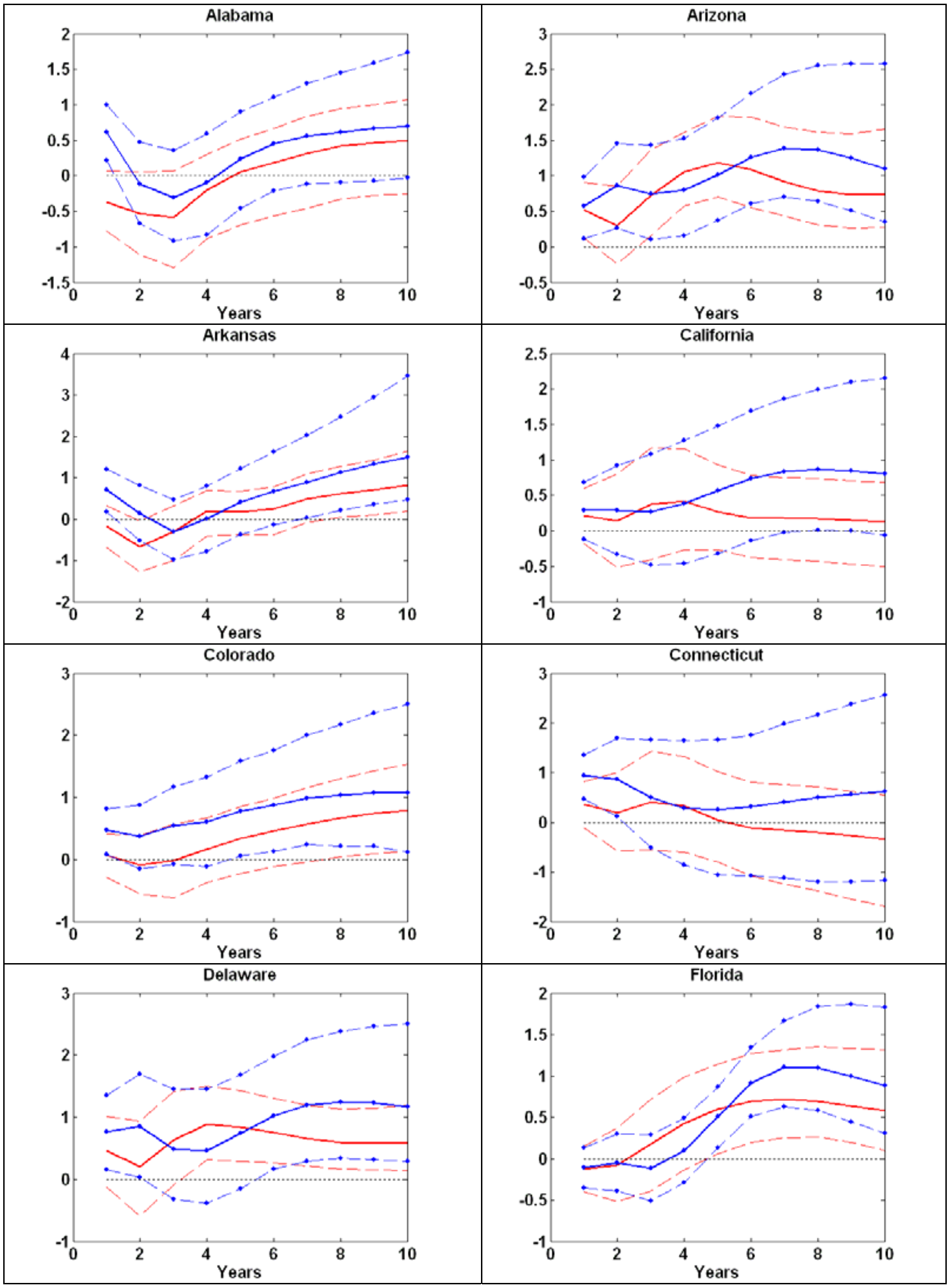
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-1997.

Figure I-12 (Continued): Productivity Responses to a Patent Shock, 1963-1997



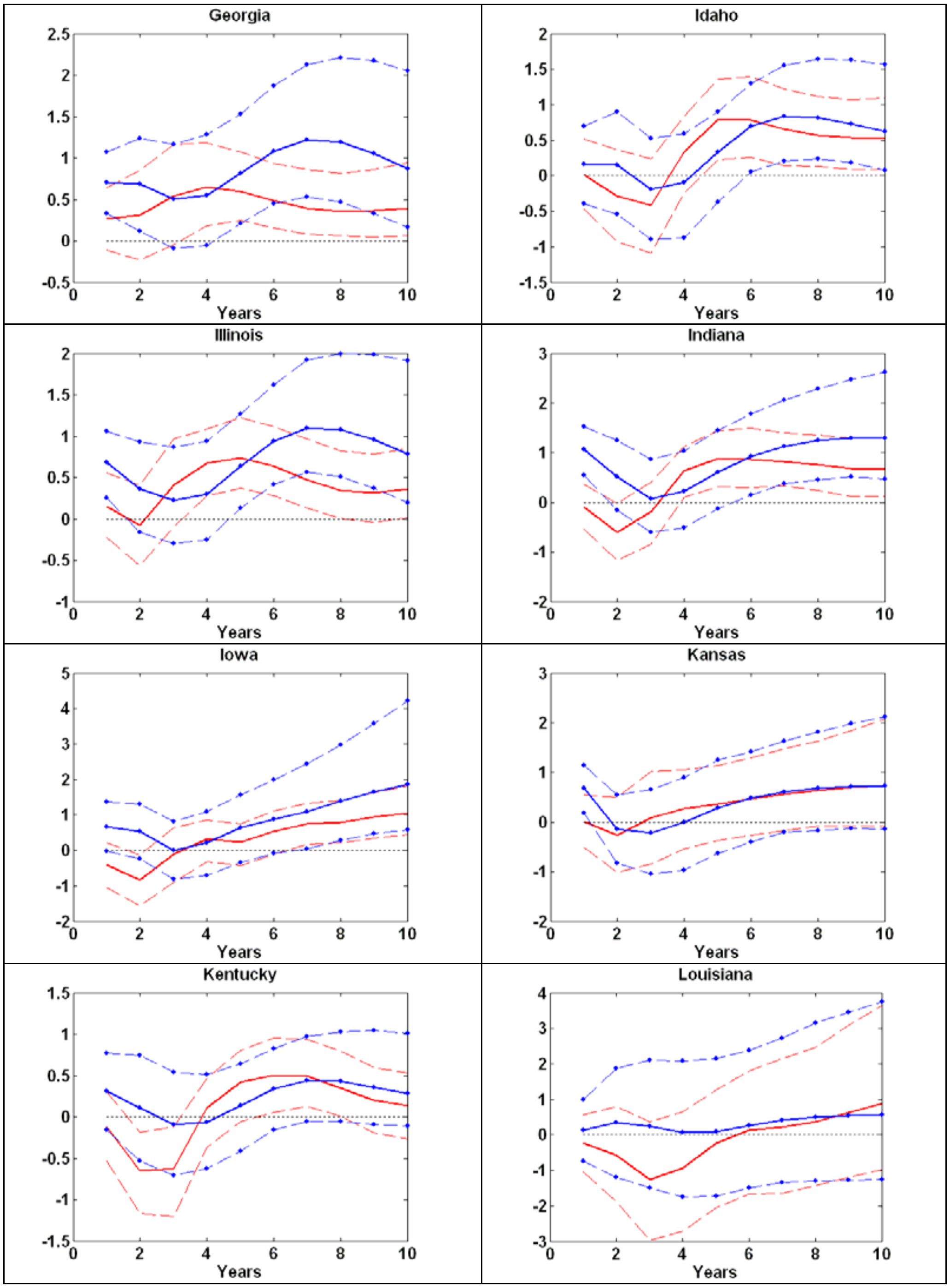
Note: The solid red line is the response function and the dotted black lines are 90% confidence intervals. The shock occurs in period 1 and the y-axis is in percent. Time Series: 1963-1997.

Figure I-12 (Continued): Productivity Responses to a Patent Shock, 1963-1997



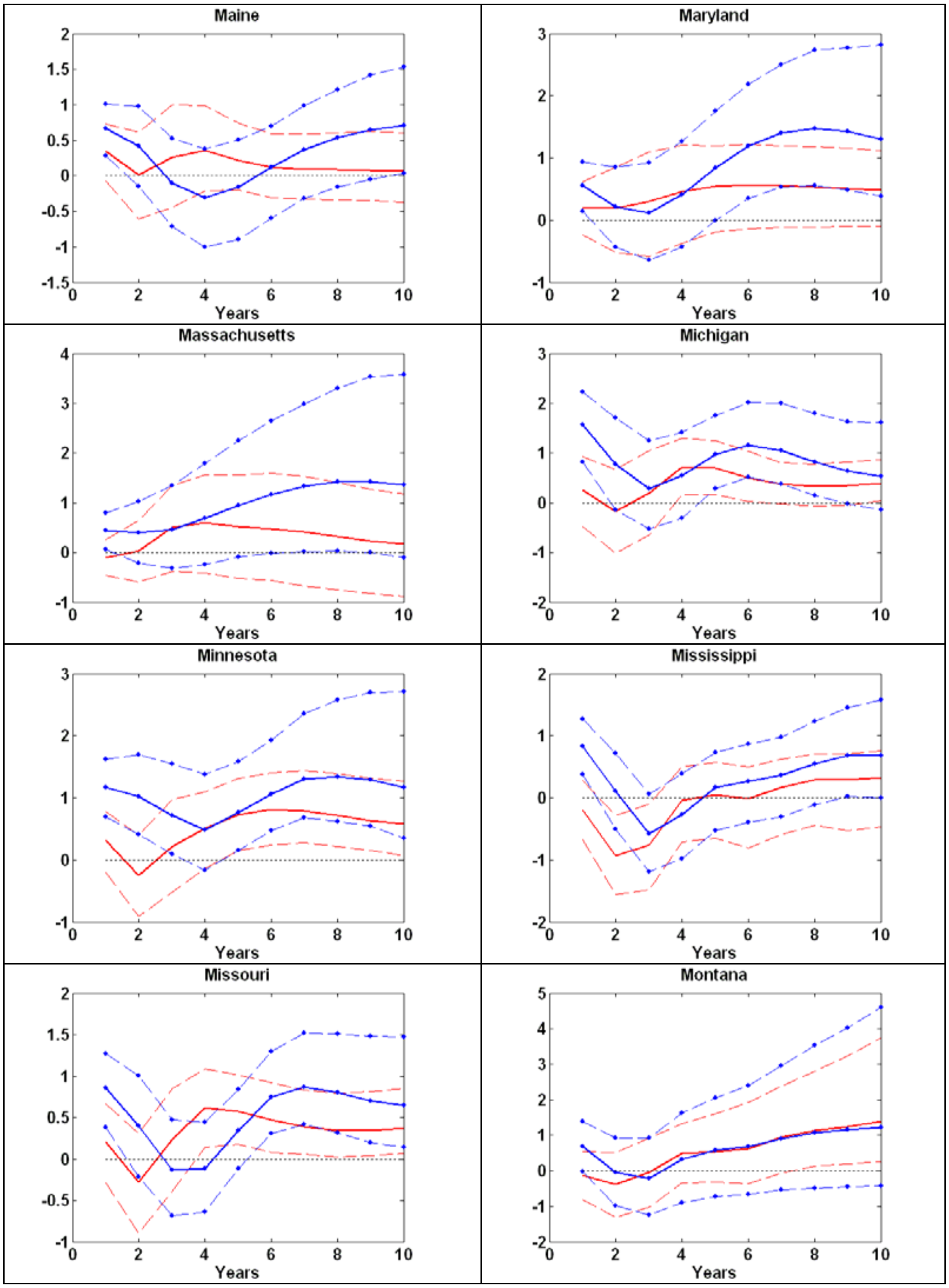
Note: The red-smooth lines correspond to the benchmark labor productivity response functions from the patent shock analysis. The blue-marked lines are results from the R&D analysis based on 1963-2004 data. The dotted lines are 90% confidence bands. The Y axis is in percent.

Figure I-13: Comparison of Productivity Responses to Patent and R&D Shocks



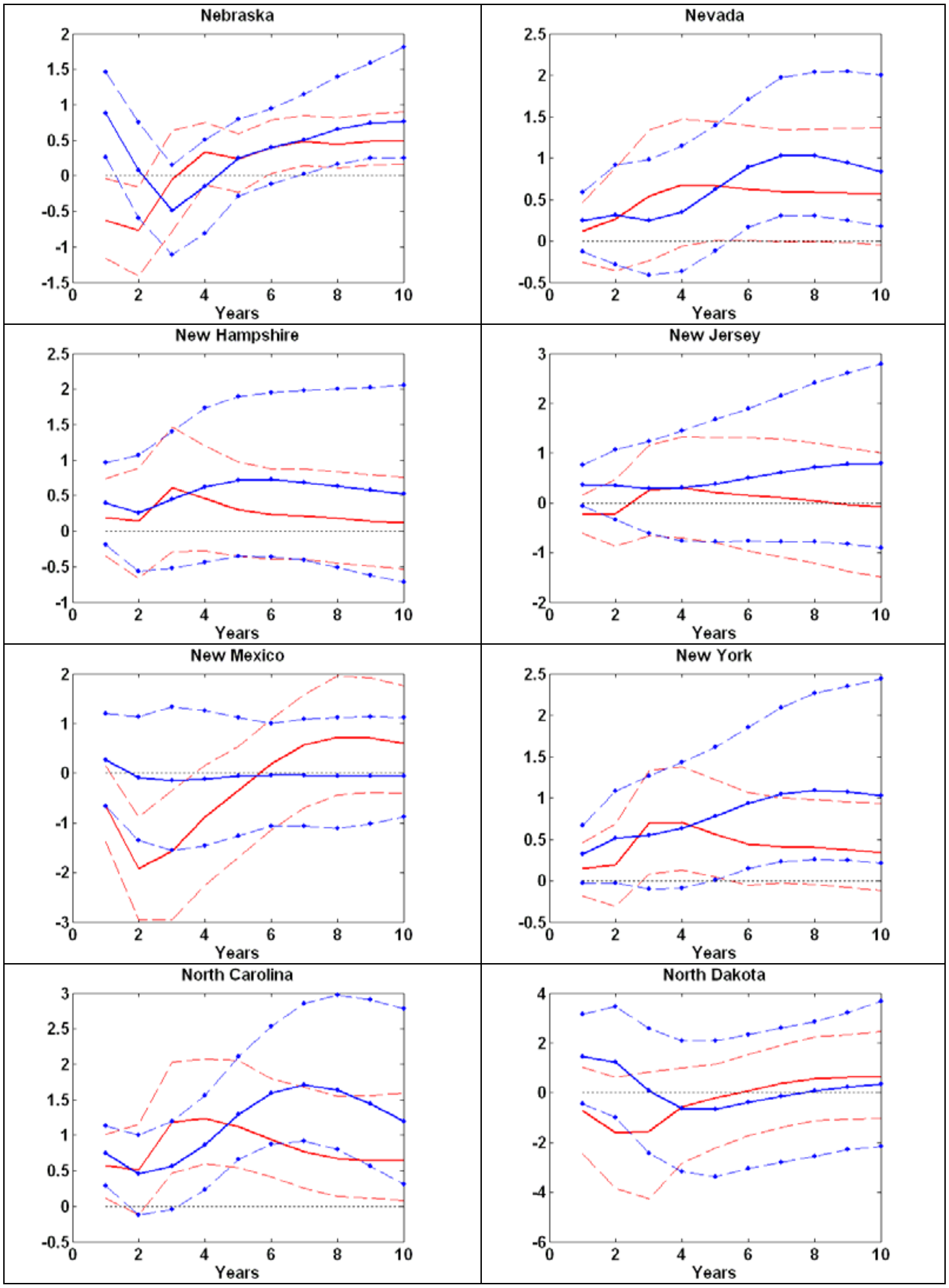
Note: The red-smooth lines correspond to the benchmark labor productivity response functions from the patent shock analysis. The blue-marked lines are results from the R&D analysis based on 1963-2004 data. The dotted lines are 90% confidence bands. The Y axis is in percent.

Figure I-13 (Continued): Comparison of Productivity Responses to Patent and R&D Shocks



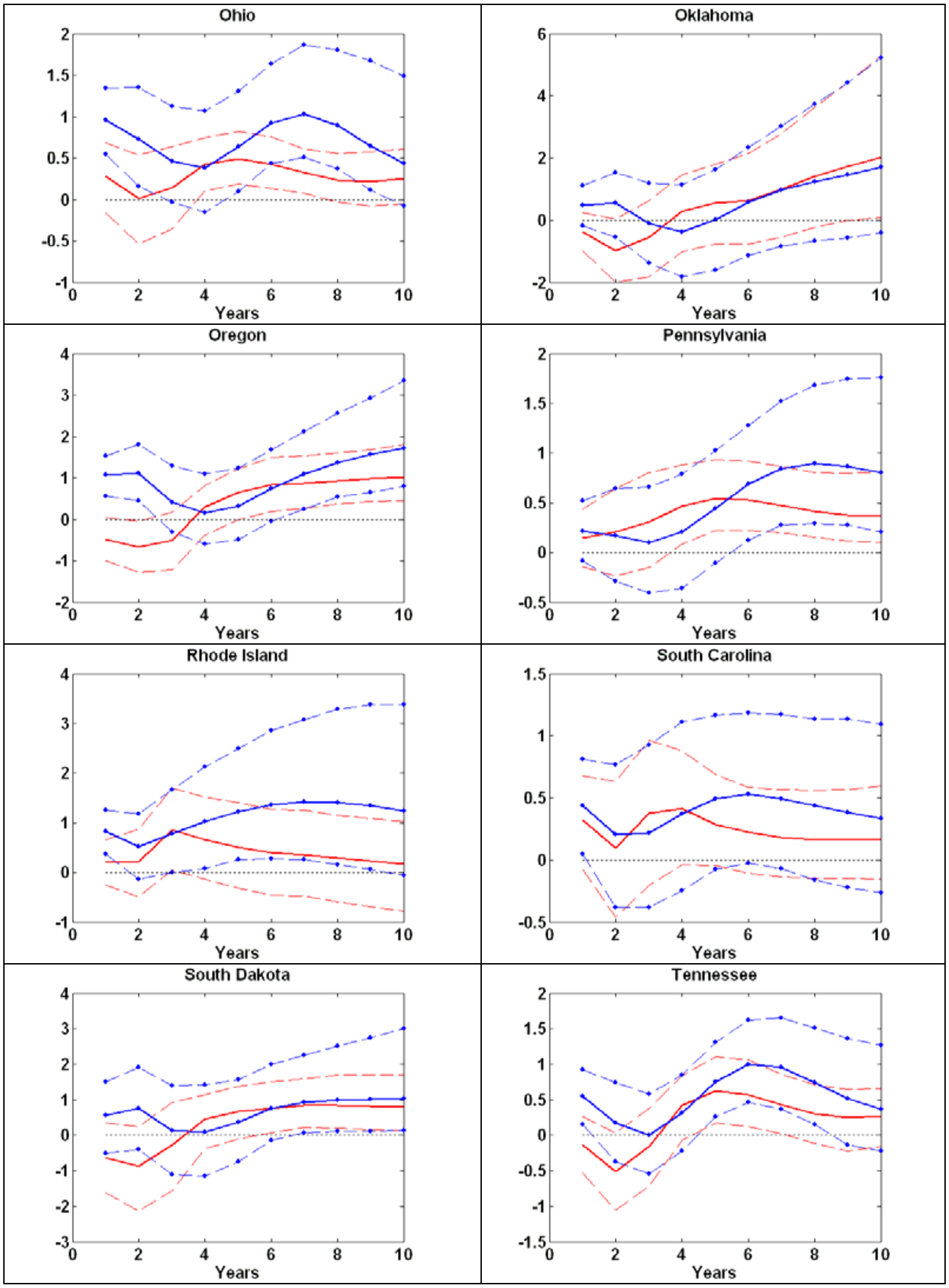
Note: The red-smooth lines correspond to the benchmark labor productivity response functions from the patent shock analysis. The blue-marked lines are results from the R&D analysis based on 1963-2004 data. The dotted lines are 90% confidence bands. The Y axis is in percent.

Figure I-13 (Continued): Comparison of Productivity Responses to Patent and R&D Shocks



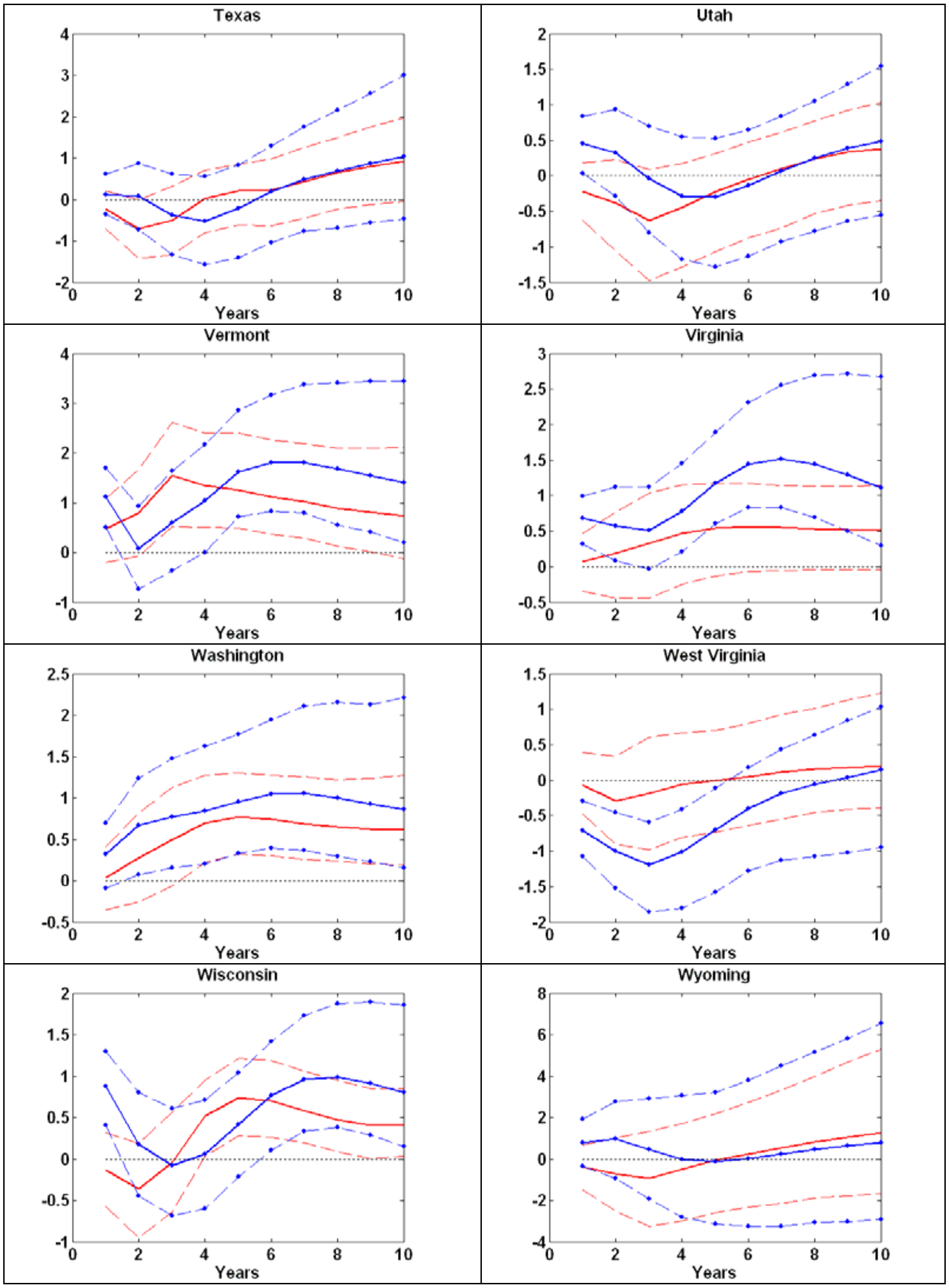
Note: The red-smooth lines correspond to the benchmark labor productivity response functions from the patent shock analysis. The blue-marked lines are results from the R&D analysis based on 1963-2004 data. The dotted lines are 90% confidence bands. The Y axis is in percent.

Figure I-13 (Continued): Comparison of Productivity Responses to Patent and R&D Shocks



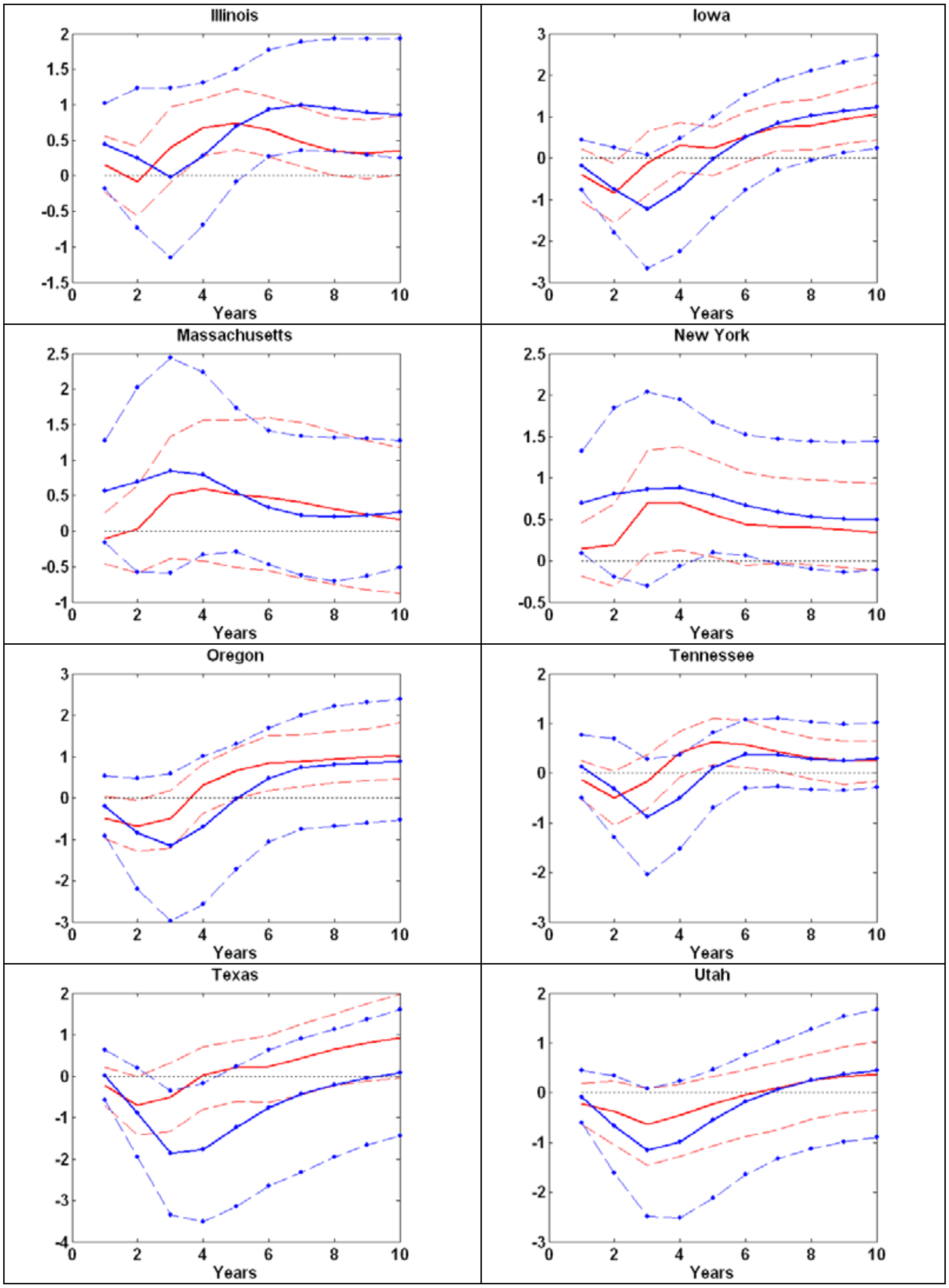
Note: The red-smooth lines correspond to the benchmark labor productivity response functions from the patent shock analysis. The blue-marked lines are results from the R&D analysis based on 1963-2004 data. The dotted lines are 90% confidence bands. The Y axis is in percent.

Figure I-13 (Continued): Comparison of Productivity Responses to Patent and R&D Shocks



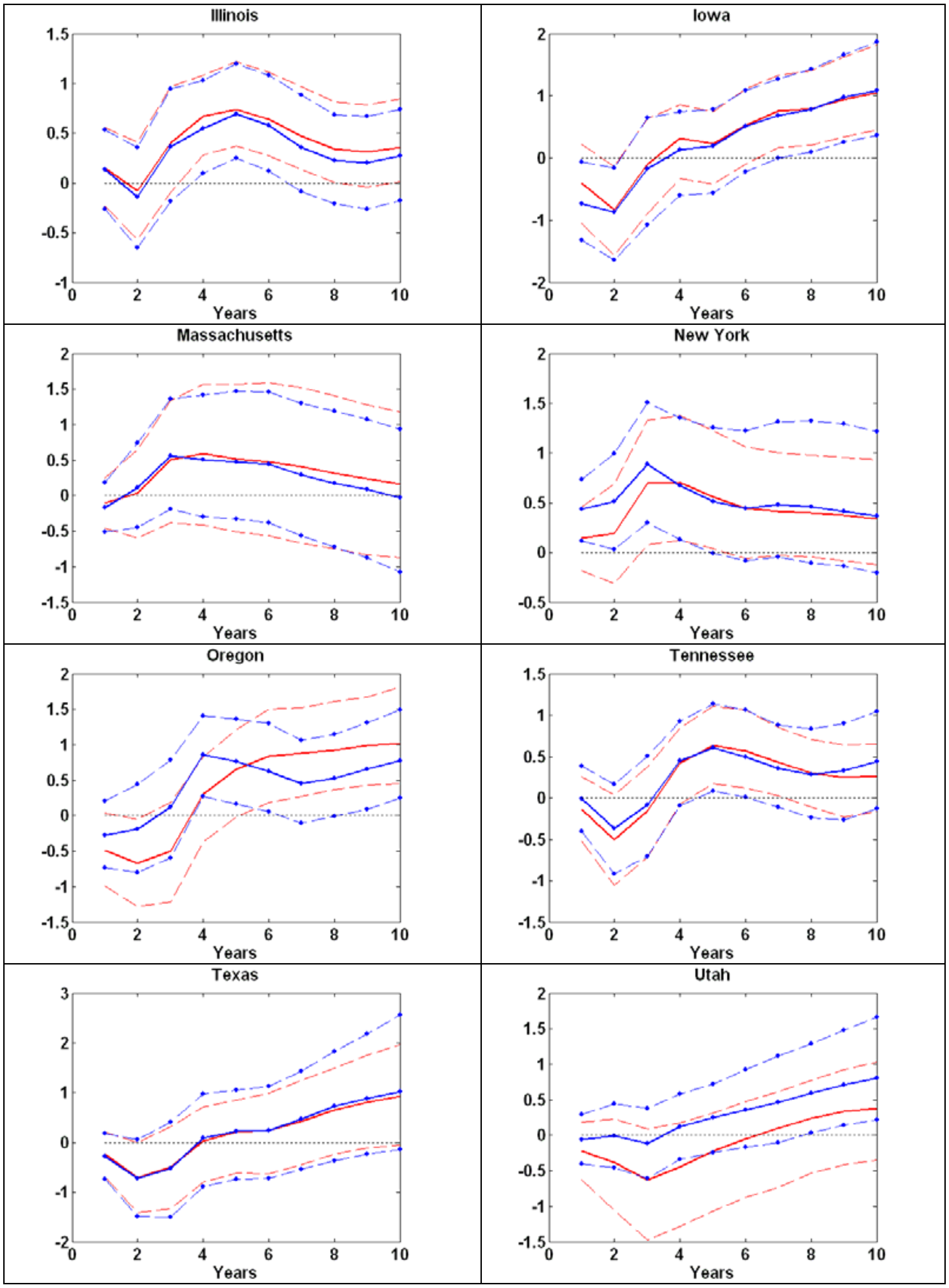
Note: The red-smooth lines correspond to the benchmark labor productivity response functions from the patent shock analysis. The blue-marked lines are results from the R&D analysis based on 1963-2004 data. The dotted lines are 90% confidence bands. The Y axis is in percent.

Figure I-13 (Continued): Comparison of Productivity Responses to Patent and R&D Shocks



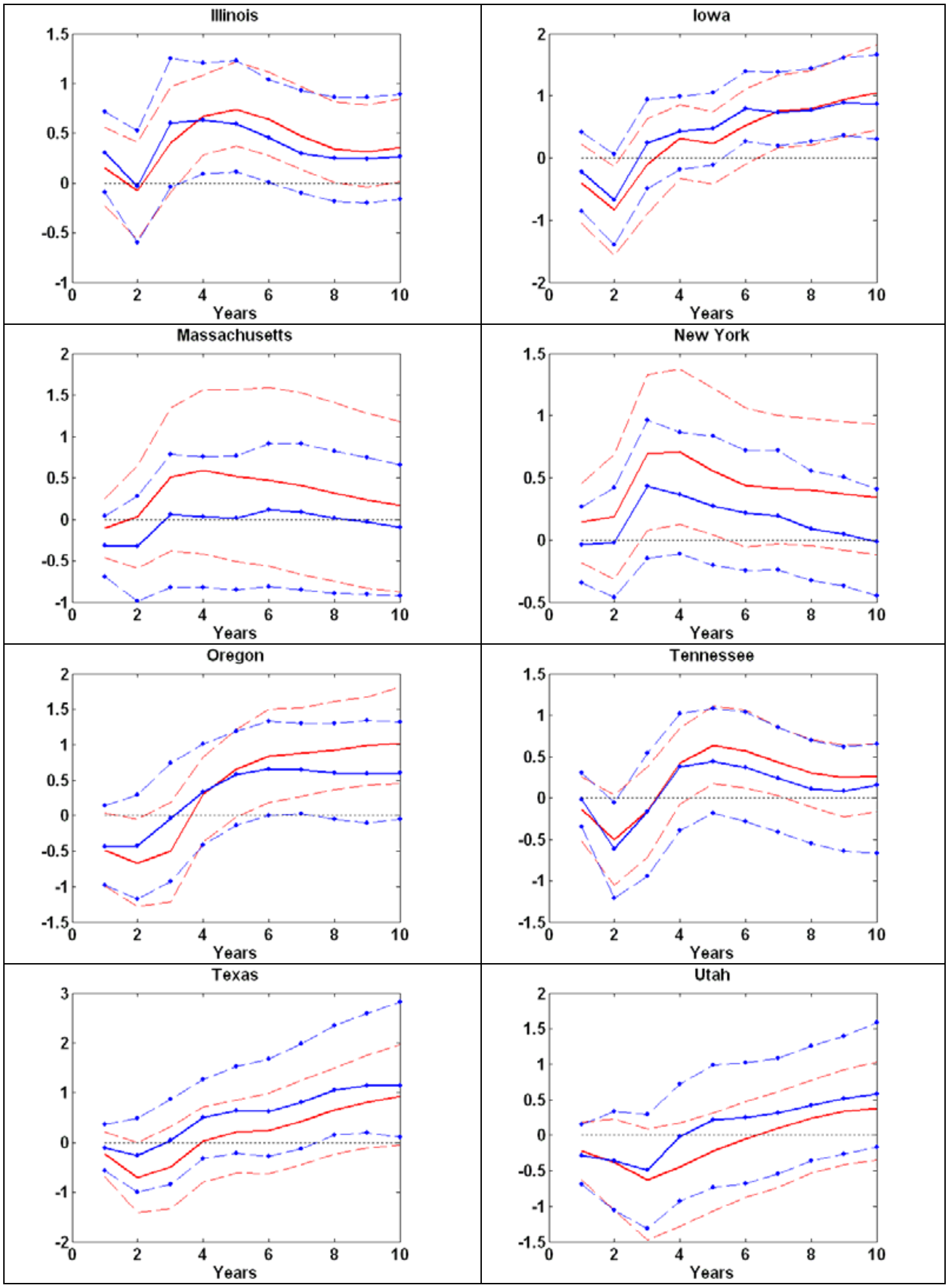
Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are state wages and salary response functions from a patent shock. The dotted lines are 90% confidence bands. The Y axis is in percent. Time Series: 1963-2005.

Figure I-14: Comparison of the Response of Productivity and the Response of State Wages to a Patent Shock



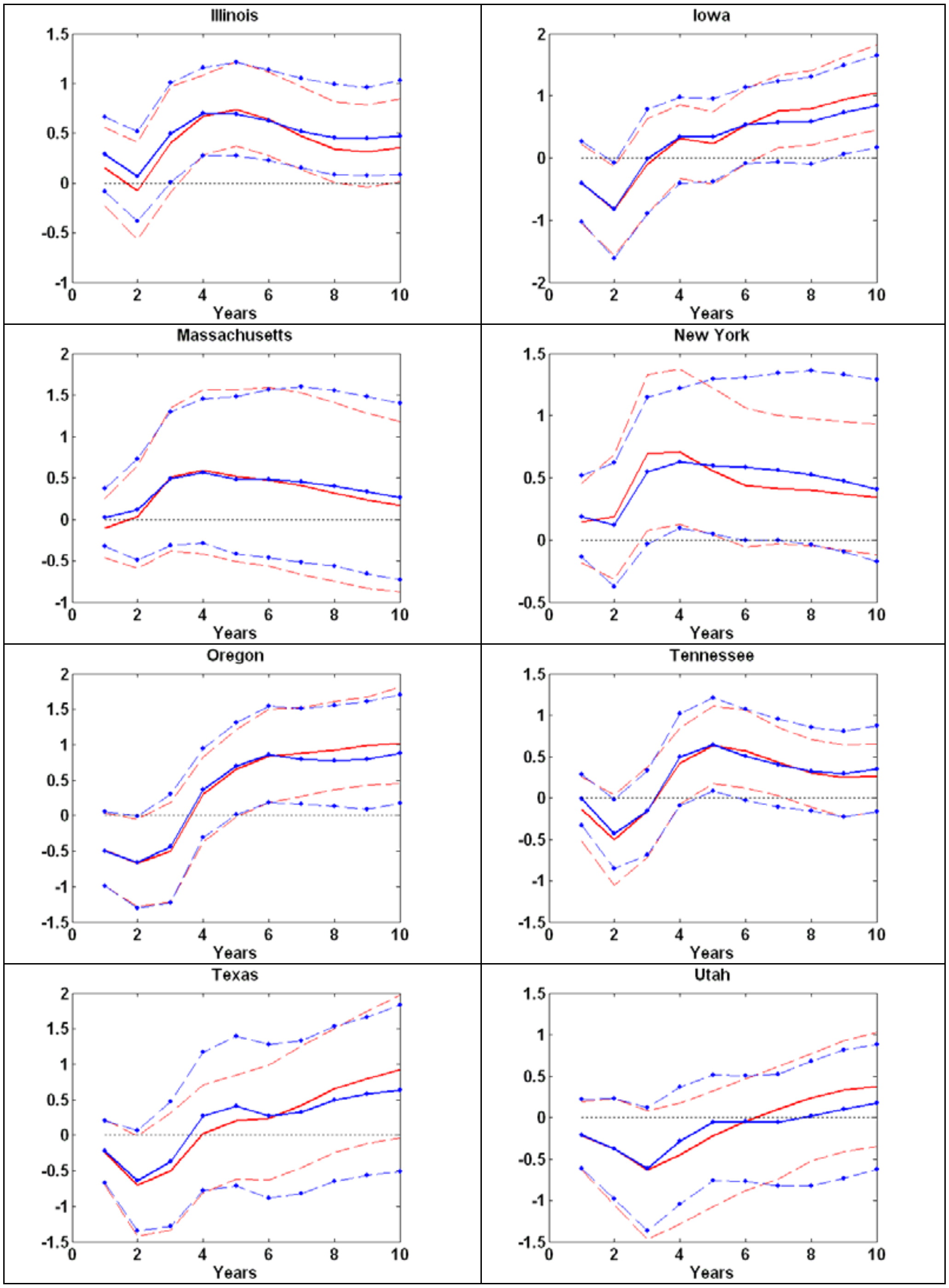
Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are productivity response functions from trivariate VARs with surrounding labor productivity as the third variable. The dotted lines are 90% confidence bands. The Y axis is in percent. Time Series: 1963-2005.

Figure I-15: Comparison of Benchmark and Trivariate Productivity Responses: Surrounding Productivity as the Third Variable



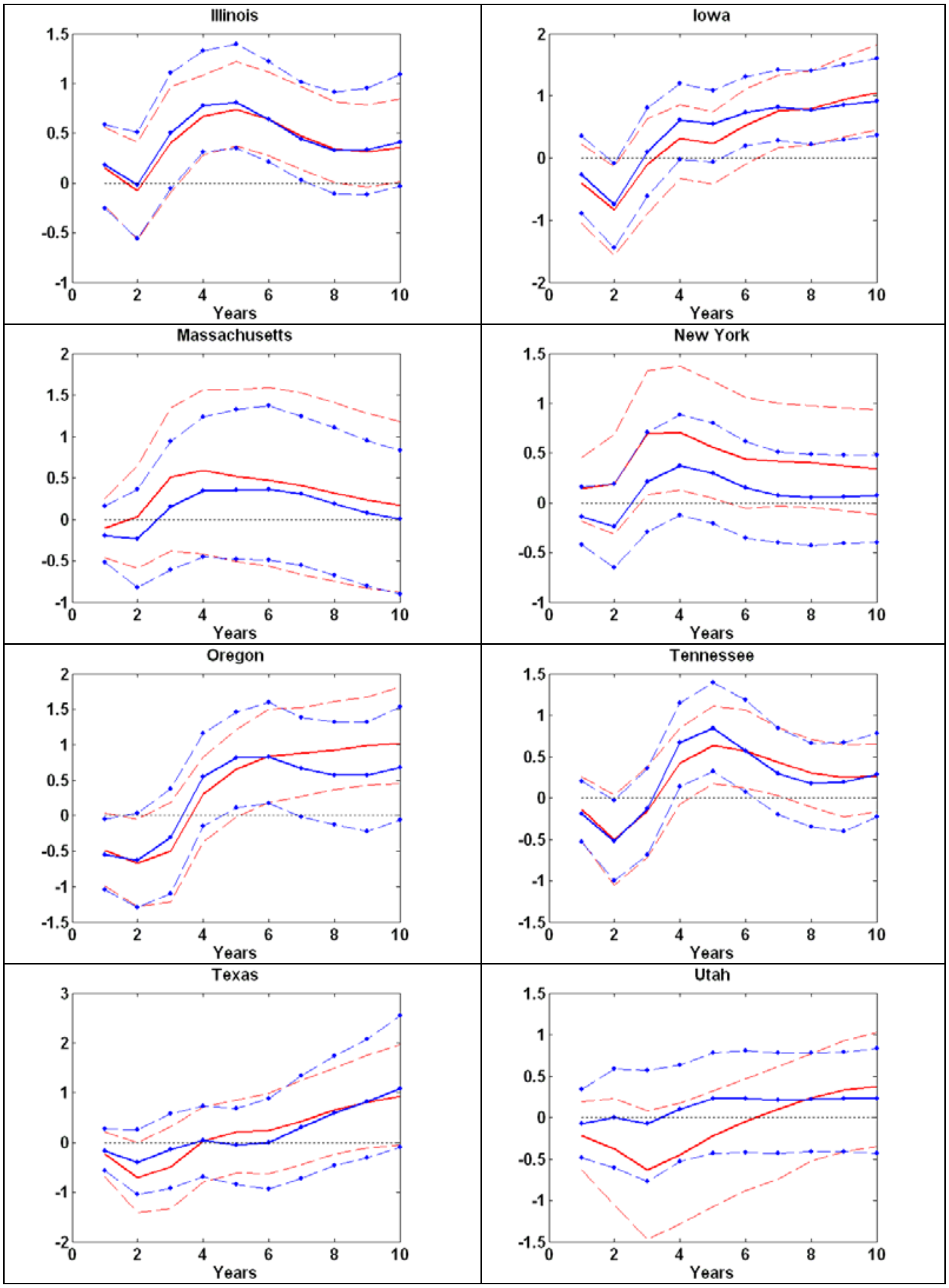
Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis using 1963-2005. The blue-marked lines are productivity response functions from trivariate VARs with BEA manufacturing employment over total BEA employment as the third variable. The time series for the trivariate VAR is 1969-2005. The dotted lines are 90% confidence bands. The Y axis is in percent.

Figure I-16: Comparison of Benchmark and Trivariate Productivity Responses: Manufacturing Employment on Employment as the Third Variable



Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are productivity response functions from trivariate VARs with real GDP by State as the third variable. The dotted lines are 90% confidence bands. The Y axis is in percent. Time Series: 1963-2005.

Figure I-17: Comparison of Benchmark and Trivariate Productivity Responses: Real GDP by State as the Third Variable



Note: The red-smooth lines correspond to the labor productivity response functions from the benchmark patent shock analysis. The blue-marked lines are productivity response functions from trivariate VARs with Density as the third variable. The dotted lines are 90% confidence bands. The Y axis is in percent. Time Series: 1963-2005.

Figure I-18: Comparison of Benchmark and Trivariate Productivity Responses: Density as the Third Variable

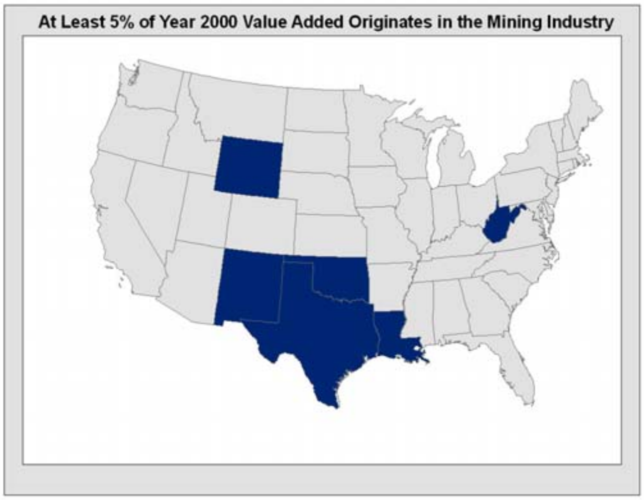


Figure I-19: Map of Oil States

I.I.3 Additional Tables

Table I-8: Cross-Sectional Analysis, Excluding Oil States

Panel A.

h	Constant	EDUhs	Diversity	Manufact	R^2
1	**3.664****	**-0.0251****	**-0.1346**	**0.0010**	0.183
	1.486	0.012	0.088	0.009	
	2.466	-2.064	-1.529	0.106	
2	**5.620*****	**-0.0455*****	**-0.1806**	**-0.0130**	0.261
	2.086	0.017	0.124	0.013	
	2.695	-2.666	-1.463	-1.017	
3	**7.193*****	**-0.0447****	**-0.2620***	**-0.0113**	0.215
	2.547	0.021	0.151	0.016	
	2.824	-2.143	-1.737	-0.728	
4	**4.3126****	**-0.0104**	**-0.1992***	**-0.0004**	0.121
	1.766	0.014	0.105	0.011	
	2.443	-0.718	-1.905	-0.040	
5	**2.1902**	**0.0038**	**-0.1192**	**0.0028**	0.053
	1.655	0.014	0.098	0.010	
	1.324	0.278	-1.217	0.276	
6	**0.5928**	**0.0157**	**-0.0618**	**0.0003**	0.056
	1.478	0.012	0.088	0.009	
	0.401	1.298	-0.705	0.035	
7	**-0.9480**	**0.0239****	**0.0067**	**-0.0033**	0.128
	1.285	0.011	0.076	0.008	
	-0.738	2.276	0.088	-0.425	
8	**-1.8615**	**0.0285*****	**0.0488**	**-0.0070**	0.207
	1.243	0.010	0.074	0.008	
	-1.497	2.798	0.663	-0.926	
9	**-2.405***	**0.0341*****	**0.0629**	**-0.0085**	0.257
	1.302	0.011	0.077	0.008	
	-1.848	3.198	0.816	-1.071	
10	**-2.890****	**0.0386*****	**0.0761**	**-0.0077**	0.274
	1.409	0.012	0.083	0.009	
	-2.052	3.346	0.912	-0.891	

Note: h indicates the impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; Diversity is the Dixit-Stiglitz index of industrial diversity; and Manufact is the share of manufacturing in a given state. The excluded oil states are Wyoming, New Mexico, Texas, Oklahoma, Louisiana, and West Virginia. Their value added originating in the mining industry is greater than 5% in the year 2000. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

Table I-8 (Continued): Cross-Sectional Analysis, Excluding Oil States

Panel B.

h	Constant	EDUhs	EDUcoll	Diversity	R^2
1	**3.2589****	**-0.0192**	**0.0099**	**-0.1444***	0.196
	1.514	0.013	0.012	0.081	
	2.152	-1.435	0.794	-1.776	
2	**3.2779**	**-0.0305***	**0.0367****	**-0.1571**	0.325
	2.047	0.018	0.017	0.110	
	1.601	-1.687	2.182	-1.429	
3	**4.559***	**-0.0245**	**0.0450****	**-0.2495***	0.294
	2.482	0.022	0.020	0.133	
	1.837	-1.116	2.199	-1.872	
4	**3.5603****	**-0.0017**	**0.0159**	**-0.2080****	0.147
	1.787	0.016	0.015	0.096	
	1.993	-0.110	1.082	-2.166	
5	**1.9316**	**0.0098**	**0.0087**	**-0.1349**	0.061
	1.693	0.015	0.014	0.091	
	1.141	0.652	0.625	-1.485	
6	**0.1025**	**0.02197***	**0.0110**	**-0.0700**	0.076
	1.503	0.013	0.012	0.081	
	0.068	1.653	0.891	-0.867	
7	**-1.5051**	**0.0273****	**0.0085**	**0.0134**	0.138
	1.313	0.012	0.011	0.070	
	-1.147	2.348	0.784	0.190	
8	**-2.565****	**0.0298*****	**0.0076**	**0.0696**	0.200
	1.283	0.011	0.011	0.069	
	-1.999	2.622	0.718	1.010	
9	**-3.219****	**0.0352*****	**0.0084**	**0.0886**	0.246
	1.347	0.012	0.011	0.072	
	-2.390	2.952	0.755	1.224	
10	**-3.540****	**0.0386*****	**0.0057**	**0.1003**	0.264
	1.458	0.013	0.012	0.078	
	-2.428	2.991	0.476	1.282	

Note: h indicates the impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; EDUcoll is the share of college educated within a state; and Diversity is the Dixit-Stiglitz index of industrial diversity. The excluded oil states are Wyoming, New Mexico, Texas, Oklahoma, Louisiana, and West Virginia. Their value added originating in the mining industry is greater than 5% in the year 2000. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

Table I-8 (Continued): Cross-Sectional Analysis, Excluding Oil States

Panel C.

h	Constant	EDUhs	EDUcoll	Diversity	Density	R^2
1	**1.4501**	**-0.0076**	**0.0089**	**-0.0871**	**0.0613**	0.214
	2.508	0.019	0.013	0.103	0.068	
	0.578	-0.407	0.714	-0.844	0.906	
2	**0.1533**	**-0.0104**	**0.0351****	**-0.0580**	**0.1059**	0.349
	3.366	0.025	0.017	0.139	0.091	
	0.046	-0.417	2.087	-0.419	1.166	
3	**0.5040**	**0.0016**	**0.0428****	**-0.1209**	**0.1374**	0.323
	4.070	0.030	0.020	0.167	0.110	
	0.124	0.054	2.103	-0.722	1.252	
4	**2.3278**	**0.0062**	**0.0153**	**-0.1687**	**0.0418**	0.154
	2.981	0.022	0.015	0.123	0.080	
	0.781	0.281	1.024	-1.376	0.520	
5	**1.8064**	**0.0106**	**0.0086**	**-0.1310**	**0.0042**	0.061
	2.834	0.021	0.014	0.117	0.076	
	0.637	0.503	0.610	-1.123	0.055	
6	**0.9127**	**0.0167**	**0.0114**	**-0.0956**	**-0.0275**	0.080
	2.511	0.019	0.013	0.103	0.068	
	0.363	0.899	0.912	-0.926	-0.405	
7	**0.9425**	**0.0115**	**0.0097**	**-0.0642**	**-0.0829**	0.184
	2.139	0.016	0.011	0.088	0.058	
	0.441	0.724	0.912	-0.730	-1.438	
8	**1.3523**	**0.0045**	**0.0096**	**-0.0546**	**-0.1328****	0.313
	1.990	0.015	0.010	0.082	0.054	
	0.680	0.305	0.969	-0.667	-2.473	
9	**1.5354**	**0.0045**	**0.0109**	**-0.0622**	**-0.161*****	0.389
	2.031	0.015	0.010	0.084	0.055	
	0.756	0.300	1.070	-0.744	-2.941	
10	**1.8132**	**0.0041**	**0.0085**	**-0.0694**	**-0.181*****	0.415
	2.176	0.016	0.011	0.090	0.059	
	0.833	0.251	0.782	-0.775	-3.090	

Note: h indicates the impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; EDUcoll is the share of college educated within a state; Diversity is the Dixit-Stiglitz index of industrial diversity; and Density is the persons per square kilometer. The excluded oil states are Wyoming, New Mexico, Texas, Oklahoma, Louisiana, and West Virginia. Their value added originating in the mining industry is greater than 5% in the year 2000. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

Table I-9: Cross-Sectional Analysis, Trivariate VAR with Surrounding Labor Productivity

h	Constant	EDUhs	EDUcoll	Diversity	Density	R^2
1	**0.1363**	**-0.0037**	**0.0113**	**-0.0411**	**0.1237***	0.265
	2.675	0.019	0.013	0.108	0.067	
	0.051	-0.193	0.856	-0.380	1.832	
2	**-3.5457**	**0.0176**	**0.0382****	**0.0270**	**0.2632*****	0.393
	3.630	0.026	0.018	0.147	0.092	
	-0.977	0.668	2.137	0.184	2.875	
3	**-2.4923**	**0.0240**	**0.0547*****	**-0.0699**	**0.2803*****	0.424
	4.127	0.030	0.020	0.167	0.104	
	-0.604	0.801	2.688	-0.419	2.692	
4	**1.0340**	**0.0156**	**0.0308***	**-0.1785**	**0.1708***	0.314
	3.602	0.026	0.018	0.146	0.091	
	0.287	0.597	1.734	-1.224	1.880	
5	**1.8666**	**0.0031**	**0.0152**	**-0.1465**	**0.1044**	0.202
	3.274	0.024	0.016	0.133	0.083	
	0.570	0.128	0.942	-1.106	1.264	
6	**0.8473**	**0.0014**	**0.0088**	**-0.0581**	**0.0498**	0.070
	2.852	0.021	0.014	0.115	0.072	
	0.297	0.070	0.628	-0.503	0.692	
7	**1.2205**	**-0.0110**	**-0.0010**	**-0.0043**	**-0.0292**	0.012
	2.319	0.017	0.011	0.094	0.059	
	0.526	-0.651	-0.088	-0.046	-0.499	
8	**1.7955**	**-0.0219**	**-0.0051**	**0.0201**	**-0.0959***	0.124
	2.087	0.015	0.010	0.084	0.053	
	0.860	-1.444	-0.500	0.238	-1.822	
9	**1.9823**	**-0.0222**	**-0.0058**	**0.0212**	**-0.1394****	0.220
	2.172	0.016	0.011	0.088	0.055	
	0.913	-1.412	-0.539	0.242	-2.544	
10	**2.1932**	**-0.0200**	**-0.0110**	**0.0159**	**-0.1676*****	0.285
	2.371	0.017	0.012	0.096	0.060	
	0.925	-1.160	-0.937	0.166	-2.802	

Note: h indicates the productivity impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; EDUcoll is the share of college educated within a state; Diversity is the Dixit-Stiglitz index of industrial diversity; and Density is the persons per square kilometer. The productivity responses are from state-level trivariate VARs with aggregate patents ordered first, state-level productivity ordered second, and surrounding productivity third. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.

* denotes significance at the 10 percent level.

** denotes significant at the 5 percent level.

*** denotes significance at the 1 percent level.

Table I-10: Cross-Sectional Analysis, Trivariate VAR with Employment

h	Constant	EDUhs	EDUcoll	Diversity	Density	R^2
1	**-0.4581**	**0.0149**	**0.0176**	**-0.0611**	**0.0834**	0.140
	2.638	0.019	0.013	0.107	0.067	
	-0.174	0.778	1.352	-0.572	1.253	
2	**-3.1325**	**0.0240**	**0.0418****	**0.0157**	**0.1180**	0.208
	3.361	0.024	0.017	0.136	0.085	
	-0.932	0.982	2.524	0.115	1.392	
3	**-1.4848**	**0.0221**	**0.0515*****	**-0.0670**	**0.0819**	0.248
	3.406	0.025	0.017	0.138	0.086	
	-0.436	0.895	3.070	-0.486	0.953	
4	**1.6685**	**0.0053**	**0.0216***	**-0.1098**	**-0.0439**	0.092
	2.503	0.018	0.012	0.101	0.063	
	0.667	0.289	1.752	-1.084	-0.695	
5	**0.4623**	**0.0093**	**0.0174**	**-0.0440**	**-0.0383**	0.077
	2.231	0.016	0.011	0.090	0.056	
	0.207	0.572	1.586	-0.488	-0.680	
6	**-0.8062**	**0.0191**	**0.0209****	**-0.0199**	**0.0043**	0.115
	1.961	0.014	0.010	0.079	0.049	
	-0.411	1.345	2.158	-0.250	0.086	
7	**-1.0209**	**0.0174**	**0.0152***	**0.0045**	**0.0066**	0.086
	1.794	0.013	0.009	0.073	0.045	
	-0.569	1.336	1.718	0.062	0.145	
8	**-0.9597**	**0.0134**	**0.0097**	**0.0226**	**-0.0017**	0.049
	1.920	0.014	0.009	0.078	0.048	
	-0.500	0.958	1.028	0.291	-0.034	
9	**-0.6697**	**0.0144**	**0.0076**	**0.0032**	**-0.0039**	0.043
	2.111	0.015	0.010	0.085	0.053	
	-0.317	0.943	0.735	0.037	-0.073	
10	**-0.0364**	**0.0154**	**0.0041**	**-0.0305**	**-0.0189**	0.063
	2.291	0.017	0.011	0.093	0.058	
	-0.016	0.928	0.364	-0.329	-0.327	

Note: h indicates the productivity impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; EDUcoll is the share of college educated within a state; Diversity is the Dixit-Stiglitz index of industrial diversity; and Density is the persons per square kilometer. The productivity responses are from state-level trivariate VARs with aggregate patents ordered first, state-level productivity ordered second, and employment third. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.

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** denotes significant at the 5 percent level.

*** denotes significance at the 1 percent level.

Table I-11: Cross-Sectional Analysis, Trivariate VAR with Density

h	Constant	EDUhs	EDUcoll	Diversity	Density	R^2
1	**-2.2275**	**0.0181**	**0.0068**	**0.0486**	**0.0670**	0.044
	2.192	0.016	0.011	0.089	0.055	
	-1.016	1.141	0.632	0.548	1.212	
2	**-5.558***	**0.0351**	**0.0270***	**0.1343**	**0.1345***	0.123
	3.199	0.023	0.016	0.130	0.081	
	-1.737	1.510	1.710	1.037	1.667	
3	**-3.569**	**0.0406***	**0.0344****	**0.0010**	**0.1325***	0.184
	3.113	0.023	0.015	0.126	0.079	
	-1.146	1.798	2.239	0.008	1.687	
4	**3.0723**	**0.0270**	**0.0092**	**-0.279****	**0.0348**	0.233
	2.801	0.020	0.014	0.113	0.071	
	1.097	1.327	0.664	-2.457	0.493	
5	**3.4686**	**0.0218**	**0.0019**	**-0.265****	**-0.0025**	0.186
	2.872	0.021	0.014	0.116	0.072	
	1.208	1.044	0.133	-2.277	-0.034	
6	**0.7186**	**0.0265**	**0.0048**	**-0.1155**	**-0.0280**	0.139
	2.668	0.019	0.013	0.108	0.067	
	0.269	1.370	0.363	-1.069	-0.416	
7	**-1.4580**	**0.0264**	**0.0046**	**0.0255**	**-0.0667**	0.196
	2.806	0.020	0.014	0.114	0.071	
	-0.520	1.298	0.334	0.225	-0.942	
8	**-3.2099**	**0.0253**	**0.0028**	**0.1428**	**-0.0812**	0.232
	3.215	0.023	0.016	0.130	0.081	
	-0.999	1.083	0.174	1.098	-1.001	
9	**-4.3871**	**0.0270**	**-0.0019**	**0.2148**	**-0.0702**	0.234
	3.587	0.026	0.018	0.145	0.090	
	-1.223	1.039	-0.109	1.479	-0.775	
10	**-4.7528**	**0.0270**	**-0.0104**	**0.2504**	**-0.0591**	0.203
	4.220	0.031	0.021	0.171	0.106	
	-1.126	0.882	-0.501	1.466	-0.555	

Note: h indicates the productivity impulse response function forecast horizon. EDUhs is the share of high school educated in a given state; EDUcoll is the share of college educated within a state; Diversity is the Dixit-Stiglitz index of industrial diversity; and Density is the persons per square kilometer. The productivity responses are from state-level trivariate VARs with aggregate patents ordered first, state-level productivity ordered second, and density third. The coefficient estimates are in bold; the standard errors are directly underneath the coefficient estimates; and the T-statistics are underneath the standard errors.
* denotes significance at the 10 percent level.
** denotes significant at the 5 percent level.
*** denotes significance at the 1 percent level.

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Chapter II

Assessing the Link between Military Spending and Productivity: Evidence from Firm-Level Data

Abstract

This chapter of the dissertation examines whether changes in military prime contract awards lead to the development of new technology and analyzes the effects on firm-level productivity. The analysis is performed using firm-level military prime contract data from the Department of Defense together with Compustat data and data from the NBER patent database in panel vector autoregressions. This allows the chapter to take into account individual firm effects. Results show that firm-level productivity, research and development, and patents increase in response to a military contract award.

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II.A. Introduction

An extensive literature has studied the consequences of increased government spending on the U.S. economy. However, economists have not reached agreement on the economic effects of military spending. Furthermore, it is commonly assumed in macroeconomic models that technological progress is exogenous to government spending. This assumption stands in sharp contrast to the fact that many new inventions originate in the defense sector and that military considerations often have led to government-financed support for development of new technological products. As is the case with the internet, which originates from federally funded defense programs, many of these inventions have later been used commercially in the private sector.

It is possible that military spending leads to an increase in privately funded research and development and to higher productivity. However, conflicting empirical evidence exists. In addition, the microeconomic literature on this topic has not sufficiently taken into account the dynamics between variables across time. Therefore, this chapter examines the effects of increased military spending on the development of new technology. The results have important consequences for modeling the evolution of a firm's production possibility frontier and for determining the aggregate economic effects.

Military spending has varied considerably during the post-World War II period. This chapter focuses on the Carter-Reagan military buildup in the 1980s, which is considered exogenous to U.S. economic fluctuations. As described in Ramey and Shapiro (1998), this buildup was initiated after the Soviet invasion of Afghanistan on December

24, 1979. This invasion led to speculations about possible repercussions in the Persian Gulf oil states, and the U.S. defense buildup became a reality. In 1979, U.S. defense spending accounted for 5.7 percent of Gross Domestic Product (GDP), and by the time of the peak[1] in 1986, it had risen to 7.4 percent of GDP. This accounts for an increase in real defense spending from 1979 to 1986 of 54.8 percent.[2] Because of this large exogenous change in military spending, large defense contractors faced considerable increases in military prime contract (MPC) awards that were unrelated to aggregate productivity.

Although the buildup was exogenous to aggregate U.S. economic fluctuations, it may be that individual awards are assigned at the firm level based on individual company performance. However, Warf and Glasmeier (1993) note that the demand for military products is highly price-inelastic and military contracts often result in cost overruns. Further, military-related companies use political lobbying in the efforts to receive military contracts. For the big defense contractors, MPC awards in the period of a big exogenous military buildup can therefore be considered exogenous to the economic conditions at the firm. This chapter discusses this issue and provides evidence that only a few of the contracts awarded to the big defense contractors are competitively procured.

Motivated by a macroeconomic question, this chapter uses U.S. data to examine the effects of military spending on the development of new technology and productivity at a microeconomic level. Specifically, this chapter of the dissertation explores whether MPC awards result in significant changes in research and development (R&D) and

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[1] The peak in real defense spending when estimated by quantity indexes was in 1987. However, as measured in percent of GDP, the peak was in 1986.

[2] Calculation is based on NIPA Quantity Indexes for real national defense spending. The overall increase in real defense spending from 1979 to 1987 was 62.2 percent. The corresponding increase in real GDP was 25.2 percent.

patenting and take into account dynamics across time through use of panel vector autoregressions (VARs). This chapter uses U.S. MPC data to examine whether firm-level productivity, stock prices, R&D, and patenting are significantly affected by increased demand in the form of MPC awards. The analysis covers the period from 1969 to 1993, which includes the large military buildup in the 1980s. With this data set, the chapter can assess how military demand translates into macroeconomic effects on productivity and can estimate the time lag until such effects are significant. These findings allow comments on how military demand shocks can affect the neoclassical model.

The analysis employs a data set of firm-level Department of Defense (DoD) contracts that have been created based on the DoD publications that list the top 100 military prime contractors and completed with aggregation of the underlying source data of the individual contracts. This chapter then provides a thorough statistical analysis of the effects of MPC on the development of new technology and on productivity. Following a positive MPC shock, we conclude that average labor productivity, which is computed as average revenue product, in a bivariate system increases after immediate positive responses of both sales and employment. The company's contribution to R&D increases a few years after the shock, indicating that MPCs lead to company efforts in enhancing the production of technology. The response of patents is considered separately for the pre- and post-1984 periods in order to account for patent policy changes that may have affected the incentive to apply for a patent. Consistent with the impulse response functions for R&D, we find that an MPC shock leads to a positive response of patent applications.

This chapter of the dissertation is organized as follows. In Section II.B., relevant existing literature on government military spending is reviewed, followed by an outline of the underlying theoretical framework. Section II.C. describes the data, and Section II.D. presents the methodology. Empirical results on productivity, stock prices, and research and development are provided in Section II.E., while Section II.F. examines the effect of an MPC shock on patenting. Section II.G. analyzes subgroups of the sample. Finally, Section II.H. concludes.

II.B. Literature

Both macro- and microeconomic studies of the economic implications of government spending have been performed. The macroeconomic studies show conflicting evidence on the response of productivity and wages to a military spending shock, while the microeconomic literature has studied government support for research and development and found conflicting results. This section reviews some of the existing literature on the subject and outlines how military demand affects the neoclassical model.

II.B.1 Related Literature

Among macroeconomic studies, Blanchard and Perotti (2002) employ a mixed structural VAR/event study approach, using institutional information from the tax system for identification purposes. They find that U.S. output is positively affected by increased government spending, while investment is negatively affected. Furthermore, when only considering defense spending, output continues to be positively affected. When considering the response of aggregate output, similar results can be found in Ramey and Shapiro (1998). They find that GDP increases following a military buildup that is identified through a narrative approach. Furthermore, total number of hours worked in manufacturing increases insignificantly after an increase in defense spending, leading to a fall in labor productivity in the manufacturing sector, while output per hour in the business sector is positively affected.

Ramey (2007) shows how the initial anticipation effect and composition of government spending into defense and non-defense spending can have dramatic consequences for the estimated effects of a government spending shock. Similar to Ramey, this chapter employs military spending data to account for the composition effect. Furthermore, this chapter uses annual financial data, which helps in mitigating any potentially omitted announcement effects.

Other papers of interest include Rotemberg and Woodford (1992), Devereux, Head, and Lapham (1996), and Edelberg, Eichenbaum, and Fisher (1999). Rotemberg and Woodford examine the effects of aggregate military spending in autoregressive models. Edelberg, Eichenbaum, and Fisher incorporate the Ramey-Shapiro buildup-dates in a VAR and confront uncertainty about the identified buildup dates. A key difference between several of these papers on government spending is the response of real wages. Rotemberg and Woodford find that real wages increase after a positive innovation to government purchases while the analysis in Edelberg, Eichenbaum, and Fisher leads to negative responses of real wages. Devereux, Head, and Lapham find in a model with increasing returns and monopolistic competition that increased government spending can lead to higher productivity and wages.

The microeconomic literature has explored the connection between government R&D spending and technological progress. Scott (1984) performs a cross-sectional study with observations from 1974 for lines of business for companies that reported to the Federal Trade Commission's Line of Business program. As such, his study is not specific to the defense business and does not take into account variation in demand across time. He finds that government subsidization of R&D does not displace private R&D spending.

Lichtenberg (1988) estimates the effects of government contracts on private R&D expenditure using firm-level panel data. However, his sample only covers a time dimension of 6 years and does not take into account patent, productivity or stock price effects. Nor does his sample period cover the drawdown in military spending in the late 1980s. With our long time dimension and estimation in a panel VAR, we are better equipped to approach a macroeconomic question and examine dynamics across time. Furthermore, the big defense contractors may act differently than small companies to a military prime contract award. Therefore, it is important to find the results from a study that mainly considers large defense conglomerates.

David, Hall, and Toole (1999) survey the literature that has examined the consequences of public R&D for private R&D. Overall, their findings are ambivalent since existing literature has found evidence of both complementarity and substitutability between public and private R&D, depending on the underlying data and methods. One study can be found in Lerner (1999). Lerner assesses the long-run success of firms participating in the Small Business Innovation Research (SBIR) program and finds that the superior growth of SBIR awardees mainly was seen for firms in areas with substantial venture capital activity. Other papers of interest include Reppy (1977), Levy and Terleckyj (1983), Saal (1999), and Wallsten (2000). Wallsten finds that public grants displace private R&D investment.

The above mentioned studies lead to the conclusion that the existing literature has not reached agreement on the effects of defense spending on economic variables such as productivity, R&D, patents, and stock prices. By having a panel data set with a long time dimension, this chapter will add significantly to the existing micro- and macroeconomic literature. With firm-level data, this study provides micro evidence for the resulting macroeconomic effects. This chapter is therefore important for understanding how macroeconomic effects arise because of underlying microeconomic decisions. It is the goal to reach a better understanding of the effects of military spending on the U.S. economy. Specifically, it is possible that military prime contracts have positive effects on the aggregate U.S. economy if the contracts lead to increased private investment in R&D. For example, if public R&D contracts allow firms to overcome fixed R&D costs then we may see a positive response of private R&D to a military prime contract. On the contrary, it may be that federal contracts substitute for private R&D that the firm otherwise would have undertaken at own cost for competitive reasons. See David, Hall, and Toole (1999) for an overview of why private R&D expenditures may be affected by public R&D contracts.

II.B.2 Theoretical Background

If MPCs lead to significantly more resources put into R&D, then firm productivity may increase over time because of the more technically advanced production process. However, the neoclassical model at the firm level generally assumes that a demand shock in the form of increased demand for defense products does not affect the production possibility frontier. Rotemberg and Woodford (1991) discuss the transmission of aggregate demand variations to the labor market in order to reconcile how government spending can lead to increased real wages.

This section follows and builds on Rotemberg and Woodford (1991) in the theoretical framework below. They note that in the case of fully competitive firms with a standard neoclassical production function, output and employment fluctuations should be associated with countercyclical movements in the real wage if the production function is unaffected by the demand shock. However, if the analysis is extended to allow for imperfect competition where firms set prices at a markup over marginal cost, then labor demand can be expressed as

$$F_H\left(K_t, H_t; z_t\right) = \mu_t w_t \, . \tag{1}$$

Here, F_H indicates the partial derivative of the production function with respect to labor input, H_t, at time t. K_t and z_t denote capital and existing technology, respectively, while μ_t signifies the markup over marginal cost. w_t denotes the real wage. With fully competitive firms, μ_t equals one. If capital and technology are taken as given, labor demand cannot shift in the short run because of a government spending shock. However, an outward shift in the labor supply curve leads to a lower real wage, corresponding to the results of Edelberg, Eichenbaum, and Fisher (1999). As mentioned above, Rotemberg and Woodford (1992) find a positive response of the real wage after increased military expenditures. To approach their finding, Rotemberg and Woodford allow for imperfect competition with varying markup. In this case, if an increase in government spending leads to a downward adjustment of the markup, then the real wage can respond positively. The labor demand curve then shifts to the right after a demand shock, and equilibrium output and labor can be positively correlated with movements in the real wage.

This chapter makes an important addition to the discussion of Rotemberg and Woodford. Specifically, since many technologies originate in the defense sector, it is possible that even with a constant markup the labor demand curve can shift out. For example, if military spending leads to the possibility of initiating R&D projects that otherwise were unprofitable, then the labor demand curve shifts out as a result. Furthermore, if company-sponsored R&D increases after a military demand shock it is likely that the production possibility frontier will shift out and productivity may slowly increase to a permanently higher level.

The defense conglomerates analyzed in this chapter are not fully competitive. It is likely that the markup either increases or decreases during a military buildup. In addition, if the increased demand leads to the development of new technology, then the production function is directly affected. The new technology can increase the range and quality of goods produced. Furthermore, the increased demand may alone result in learning-by-doing effects that increase the marginal product of each worker and thereby expands the production possibility frontier.

The optimality condition in (1) can be expanded by including other factors that can affect the production of goods. We allow the technology variable, z_t, to depend positively on past R&D efforts. The condition then becomes

$$F_H\left(K_t, H_t, z_t\right) = \mu_t w_t \quad \text{where } z_t = Z(RD_{t-1}).$$

If the government contract includes R&D contracts, then the level of technology at the firm can be positively affected.

The purpose of this chapter is to examine the effects of military prime contracts on economic factors. By examining firm-level labor productivity, sales, employment, stock prices, and the development of new technology, we can infer about the overall macroeconomic consequences of military prime contract spending.

II.C. Data

The selection of firms is based on various issues of the Department of Defense publication "100 Companies Receiving the Largest Dollar Volume of Prime Contract Awards." This publication lists the top 100 military prime contractors that receive MPC awards in any given fiscal year. Thus, the analysis includes firms whose main business relies on military prime contracts. However, several firms enter and exit the top 100 list over time. To create a complete time series this chapter aggregated the raw data on MPC awards at the firm level, collected from the Department of Defense Statistical Information Analysis Division website. These data contain a complete list of all individual contracts awarded during the sample period (1969-1993).

The raw data reveal that the number of contracts received by any one firm varies considerably among companies. In addition, a large defense company, with subsidiaries, may receive more than 2000 contracts annually. To find the total dollar value of contracts at an annual level for each firm, the contracts were aggregated for each fiscal year[3]. Chapter III of this dissertation contains a thorough description of this underlying data set,

[3] The fiscal year for the United States government lasts from October 1 of one year through the end of September of the following year. For example, fiscal year 1977 covers October 1976 through September 1977. Prior to 1977, the fiscal year was defined as July through June.

although that approach aggregates the data at the spatial level. In order to convert the military contracts into real values, the MPC data were deflated with the GDP deflator.

It is likely that pricing of MPCs does not grow with the rate of inflation as measured by the GDP deflator. Therefore, this study tried using a price index for national defense consumption expenditures and gross investment as an alternative deflator. However, this series is only available starting in 1972. As such, using this series limits the time dimension of the analysis. The overall results were not sensitive to using this deflator instead of the GDP deflator, and these estimations are therefore not shown.

One potential issue is that the timing of MPC awards may be important in explaining the results below. It is likely that companies have advance information on forthcoming contract awards, and the identified military shock may therefore not fully take into account expectations. However, the use of annual data mitigates the anticipation effect. Additionally, this chapter has tried including stock prices in all the computations below. This should account for any expectations formed prior to receiving the MPC. Including stock prices in the analysis did not change the conclusions, indicating that the timing of the MPC awards is not important in explaining the results.

Data on total sales, employment, stock prices, and R&D at the firm-level fiscal year were collected from the Compustat database. Some defense contractors are unavailable in Compustat, while others only have a few years of observations. To maximize the number of observations, the annual time series extends over the period 1969-1993. This allows for the inclusion of the Carter-Reagan military buildup in the 1980s. Furthermore, the analysis allows for an unbalanced panel of firms in order to increase the sample size as not all firms cover the full sample period. This procedure yields a panel of 45 firms, which includes major defense contractors such as Boeing, Grumman, Lockheed, McDonnell Douglas, Northrop, and Raytheon. Table II-1 lists the full set of firms in the sample.

The aggregate real MPC value for the selected companies is depicted across time in Figure II-1 together with total aggregate real U.S. MPC values. The graph clearly shows how the firm-level data capture the overall military buildup, and the contracts for the selected firms account for approximately fifty percent of total U.S. MPCs. As such, we can be confident that the defense spending faced by these firms relates to the exogenous Carter-Reagan military buildup.

The data include the closing values of January stock prices, deflated using the GDP deflator. Data on value added is not directly available in Compustat. Therefore, this chapter uses the average revenue product as a proxy for labor productivity data. The average revenue product, which the chapter will refer to as labor productivity, is computed as nominal sales deflated by the GDP deflator and divided by the total number of employed workers for the given company. The chapter uses linear interpolation for the employment and R&D series where a few observations are missing. This is the case for very few observations and is not important for the analysis. Company R&D is deflated with the GDP deflator. It is important to note that R&D expenses account for the company's contribution to R&D. Government-sponsored R&D is therefore not included in this variable. For a few companies, government-sponsored R&D is included in single years. After examining the data, we find that this issue is not the main factor in explaining the results.

Patent data are collected from the NBER patent database, which consists of utility patents granted between 1963 and 1999. Hall, Jaffe, and Trajtenberg (2001) describe this data set. For the analysis, the patent data are sorted by application year since variation in budgetary resources at the United States Patent and Trademark Office (USPTO) leads to changes in the application-grant lag over time as explained in Christiansen (2008). Since we are interested in examining the effects of government spending on the development of new technology, using the application year corresponds to employing the data most closely associated with the date of invention.

Because of the time lag from the date of application until the date of grant, the last few years of the dataset contain a decrease in the patent application count because of data truncation. As an example, patents granted in 2000 or later but which had an application date in 1999 or earlier are not counted in the sample. Because the sample period ends in 1993, this issue does not lead to severe truncation problems with the patent application data. In the patent analysis, firms are included if they have at least one patent application in every year during the given firm's sample length. This leaves 39 companies when using the patent application series.

In 1980, President Carter changed the patent policy for small businesses, and in 1983 this was expanded to include all firms. Before 1983, the federal government had the exclusive rights to patents of large businesses achieved because of federally funded research. Therefore, firm-level patent data in the sample may not be directly comparable before and after 1983. In order to account for this, the chapter also splits the sample in 1984 when examining the response of patents to a defense shock. See Eisenberg (1996) for a discussion of this change in patent policy.

Collection of the mentioned variables results in an annual unbalanced panel of data on MPCs, R&D spending, productivity, employment, sales, patents, and stock prices over the period 1969-1993 for up to 45 firms. The natural logarithm is taken of all variables. A few firms in the underlying data set merge during the sample period. In most of these cases, this chapter treats the merging firms as one firm over the full sample period. The chapter also tried excluding big merging firms from the sample without affecting the conclusions.

It is important to address the fact that military prime contracts may be awarded at the firm level based on the economic performance of the firm. To examine this possibility we obtained data from the Center for Public Integrity. These data contain information about the conditions under which MPCs were awarded at the firm level during 1998-2003. Table II-2 reports results from a selection of the large military prime contractors in the sample. The selection is based on the criteria that data are available from Center for Public Integrity and that the given firm is among the top contractors in the sample in this chapter. Because of data limitation, the table is based on data from 1998 to 2003. The chapter thereby assumes that the nature of the award method was unchanged between the 1980s military buildup and the military spending in the late 1990s.

Table II-2 also shows that these firms largely receive MPCs that have not been put out for competitive bids - mainly a result of being the sole source for the demanded military product or service. Furthermore, companies that primarily have been awarded contracts through full and open competition receive a substantial part of the contracts after a bid with only one or two bidders for the contract. Oil companies (not included in the table) are for the most part awarded contracts through full and open competition, but most often with only two bidders. These contracts are mainly fixed price contracts. Overall, this chapter finds strong evidence that MPC awards are given to the top military prime contractors primarily without strong competitive pressure.

One potential concern is that firms may be awarded the contracts based on existing ideas for new technological inventions that only will be implemented after the contract has been awarded. If this is the case, the military shock considered in this chapter may contain unresolved endogeneity. However, the analysis suggests that this issue is not the main driving factor behind the results. Additional evidence for this can be found by studying the individual firm-level time series of MPC awards. If existing technology at any given firm were the basis for distribution of MPC awards then we would expect the dollar value of MPCs for each firm to peak in very different years. Indeed, the vast majority of firms in the sample depict MPC award series that have either a local or a global maximum in the early to mid-1980s, corresponding to the aggregate military buildup. Figure II-2 plots a sample of the firm-level military prime contract series. In this figure, the dollar value of military prime contract awards peaks in the mid-1980s. Small differences in the peak year between the firms are anticipated as it is expected that government demand for different military products changes across time during the build-up. Therefore, based on the evidence provided, the analysis concludes that MPC awards for the given selection of firms are exogenous to firm-level productivity and technology.

II.D. Methodology

Let N denote the total number of firms in the panel and T_n the number of time periods for firm n. This chapter estimates an unbalanced panel vector autoregression (PVAR) with p lags and m variables. The basic unbalanced PVAR looks as follows:

(2) $$w_{nt} = c + \sum_{l=1}^{p} \Phi_l \cdot w_{nt-l} + e_{nt}$$

$$e_{nt} = \lambda_t + \alpha_n + \varepsilon_{nt}, \qquad \text{where} \quad \varepsilon \sim N(0, \Omega)$$

and $$E(\varepsilon_{nt}\varepsilon_{rs}^{'}) = \begin{cases} \Omega & \textit{for } n = r,\ s = t \\ 0 & \textit{otherwise} \end{cases}$$ for $t = 1, \ldots, T_n$ and $n = 1, \ldots, N$.

w_{nt} is an $m \times 1$ vector of variables for firm n at time t. Φ_l, for $l=1,..,p$, is an $m \times m$ matrix of coefficients and c is a constant term. λ_t is a constant term that is common across firms but varies across time. This is included in order to take into account aggregate macroeconomic effects that may affect profitability of the firms across the business cycle. α_n is a firm-specific effect, which is constant across time but varies across firms. This allows for individual effects that influence the firms differently. Lastly, ε_{nt} is a vector of errors. We assume homogeneity across firms such that the variance-covariance matrix, Ω, is common for all firms across time. Both α_n and ε_{nt} have zero means and are independent among themselves and with each other.[4]

[4] Standard errors are estimated by Monte Carlo with 2000 simulations. However, we also estimated (not shown) standard errors, following Cao and Sun (2006). This method takes into account that when T is short, the usual asymptotic results for orthogonalized impulse response functions are not applicable but may lead to standard error bands that are too narrow.

To estimate the system, we remove the aggregate time effect and the constant term by subtracting the mean across firms from all observations. This yields the following equation:

$$w_{nt} - w_{\bullet t} = \sum_{l=1}^{p} \Phi_l \cdot \left(w_{nt-l} - w_{\bullet t-l} \right) + \alpha_n - \alpha_{\bullet} + \varepsilon_{nt} - \varepsilon_{\bullet t} .$$

Let $y_{nt} = w_{nt} - w_{\bullet t}$, $c_n = \alpha_n - \alpha_{\bullet}$, and $u_{nt} = \varepsilon_{nt} - \varepsilon_{\bullet t}$, then the equation can be written as

(3) $$y_{nt} = \sum_{l=1}^{p} \Phi_l \cdot y_{nt-l} + c_n + u_{nt} .$$

This system is estimated by OLS where the individual effects are estimated. In general, under the assumption of a fixed T and $N \to \infty$, the OLS estimator is inconsistent. Under this assumption the system can be estimated using the Anderson-Hsiao estimator.[5] However, if we assume big T then the model can be consistently estimated by OLS. For our sample length of up to 25 periods, T is assumed sufficiently large to not cause problems with OLS inconsistency or with narrow standard error bands as discussed in Cao and Sun (2006).[6]

II.E. Empirical Results

The benchmark model is a bivariate unbalanced panel VAR with D_{nt} and MPC_{nt}. Here, D_{nt} indicates a variable that changes according to the measure of interest, and MPC_{nt} denotes the log-level of MPC awards for firm n at time t. These variables enter the system in the aforementioned order. When D_{nt} denotes the log-level of labor productivity

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[5] We estimated the system by GMM with Anderson-Hsiao instruments. However, the restrictive moment conditions together with the relatively small N lead to GMM results that are sensitive to changes in the lag-length.

[6] We consider scenarios with more than 10 years of annual data, which suggests that the Cao-Sun standard error adjustment is small. Indeed, preliminary results show this to be the case.

(LP), R&D (RD), or patents (PAT) this ordering allows for changes in productivity or technology to lead to MPC awards in case a contract is awarded through competitive bidding to the most productive firm. However, since the Cholesky short-run restriction may be sensitive to the ordering of the variables, the impulse response functions were also computed ordering the MPC variable first in the system. Other variables such as the number of employed workers (EMP), total sales (SALE), and stock prices (SP) were also included in the system in place of D_{nt}. The natural logarithm was taken of all variables.

Before estimating the system, the appropriate lag-length must be chosen. The Akaike Information Criterion suggests using one lag. However, since military contracts may last longer than one year, only including one lag may introduce omitted variable bias. This chapter therefore experiments with different lag lengths and chooses to include three lags in the benchmark analysis.

The impulse response functions from a bivariate model with different variables and 90 percent confidence intervals are illustrated in Figures II-3 through II-7, using 45 firms for the estimation, except in the case of R&D where 43 firms are included because of data limitations. In a bivariate VAR with LP and MPC, an MPC shock leads to temporary effects on MPC awards and labor productivity increases during several years after the shock. Panels A and B of Figure II-3 depict results of including two and three lags, while Panel C presents impulse responses with MPC ordered first in the bivariate system. Changing the lag length does not change the overall conclusions. The very long-lasting response functions indicate a possible expansion of the production possibility frontier of the firm over time. When LP is ordered first in the system, MPC awards do not increase significantly after a productivity shock, although ordering MPC first in the

PVAR does lead to a temporarily significant and positive response. With MPC placed first in the PVAR, productivity slowly increases to an insignificantly higher level.

The increase in productivity after an MPC award results from immediately positive and very persistent responses of both sales and employment (Figures II-4 and II-5), over time leading to an increase in productivity as a result of the relatively stronger response of sales. Although the MPC in itself leads to higher sales since the contract payments are included in the sales measures, it is not clear that this would lead to positive effects on productivity as employment must be adjusted in order to account for the increase in production demands. The impulse response functions indeed indicate that MPCs over time can be very beneficial to the contracting firms.

With productivity increasing after an MPC shock, we expect this to be realized in the stock price. Indeed, Panels A and B of Figure II-6 show that stock prices with different orderings of the data respond positively to an MPC shock and the responses depict very long-lasting effects. Additionally, there is no evidence that military prime contracts are awarded to firms with a high stock price value, as the response of MPC to a stock price shock is not statistically different from zero at any horizon. This further supports the notion that MPCs are exogenously awarded. If military prime contracts were given based on the economic conditions at the firm, we would expect that a stock price shock, indicating an economically strong firm, would lead to MPC awards for the given firm. We do not find evidence of this.

That stock prices slowly increase to a higher level indicates that the future positive effects of MPC awards are not capitalized immediately. This may be a result of uncertainty about the development of future technology. For comparison, in the most recent military buildup, stock price analysts at CNN Money[7] found that a portfolio of defense stocks experienced a gain of about 78 percent over the two and a half years following the invasion of Iraq in 2003. During the same period, the S&P gained 39 percent. That the defense stocks outperformed the market also during the Iraqi war is consistent with the fact that stock prices increase over several years also in this chapter's analysis.

In a bivariate PVAR with R&D and MPC (Figure II-7), the R&D response to an MPC shock becomes significantly positive a few years after the shock. In addition, with three lags in the PVAR, there is no significant effect of an R&D shock on MPCs. However, this response does become significant at the long horizon for some choices of lag lengths (not shown). This gives an indication that MPCs to some extent may be awarded to firms that have spent resources into developing a new technology. The fact that military prime contracts, which themselves include funding for R&D, lead to an increase in company-financed R&D is a very interesting result. This finding adds to the existing literature by showing how the main response of R&D does not occur immediately; allowing for time dynamics, as done in this chapter, is very important.

Some of the results in the bivariate analysis may be affected by omitted variable bias if too few variables are included in the empirical model. Figures II-8, II-9, and II-10 therefore display impulse response functions from a trivariate system of equations with three lags. The response of R&D to an MPC shock is unchanged when considering a trivariate system with R&D, LP, and MPC in Figure II-8, clearly showing how more resources are put into research and development when MPCs are awarded. Furthermore,

[7] CNN Money.com, November 10, 2005.

any positive effects on MPC awards of labor productivity shocks are not present in the trivariate analysis. This provides further evidence that military prime contracts are not awarded to the firm with highest productivity. Interestingly, an MPC shock in the trivariate system in Figure II-8 only leads to insignificant effects on productivity.

Panels A and B of Figure II-9 shows the responses from a trivariate system with SP, R&D, and MPC with different lag lengths. The third columns of the figures depict how an MPC shock continues to lead to positive responses of SP and R&D. Additionally, Figure II-10 reports results from a PVAR with SP, LP, and MPC, using two (Panel A) and three (Panel B) lags. Here, a military prime contract shock leads to positive responses of both SP and LP, as was the case in the bivariate analyses. Although this chapter chooses to order SP first in the trivariate system, the result is robust to ordering SP last.

This section has shown that stock prices, R&D, and in most cases productivity increase significantly following a military prime contract award. Furthermore, the analysis supports the assumption that MPCs are not distributed based on the economic conditions at the firm. However, there is some evidence that firms with increased spending on R&D tend to receive a higher number of contracts a few years after the R&D expense when new technologies have become productive.

II.F. Patenting

In 1980 President Carter approved the Bayh-Dole University and Small Business Patent Procedures Act (35 USC §§200-211). This implied a change in profitability of inventions from defense contracts. Before 1980, the rights to an invention made with federal funding belonged to the U.S. government. In 1980, it became possible for universities and small businesses to retain title to inventions that were funded under federal R&D contracts, assuming that the federal government is granted a non-exclusive, non-transferable license to practice the given invention. However, most firms in the sample in this analysis are large publicly traded firms. We therefore choose to split the sample in 1984 after President Reagan, in 1983, extended the policy to include all contractors, regardless of size.

This change in patent policy increased the incentives to invent and innovate based on defense contracts as inventions originating from these contracts became profitable through the option of collecting royalties. It is very likely that patenting at the firm level for these contractors changed substantially and inventive activity increased because of this policy change. To take this issue into account, this chapter estimates the effect of MPC awards on the number of patent applications in the two sub-periods of the sample.

The number of patents per firm in any given year varies considerably across firms. Table II-3 lists the number of average annual patents for the selection of firms in the patent sample. The average number of annual patent applications is higher in the post-1984 period, compared to the earlier period. However, a few of the technology firms are very important in explaining this difference: Hewlett-Packard, IBM, Motorola, and Texas Instruments all experienced a big increase in patenting between the two periods. It is therefore not clear that the change in patent policy is important for the full sample of firms.

It should be noted that the total annual number of U.S. patent applications started to increase in the mid-1980s. However, Kortum and Lerner (1998) have examined this issue and find that the surge in patenting was not specific to U.S. patent law changes. We can therefore contribute this change to an increase in overall U.S. scientific discovery. The finding of an increase in patenting for four of the technology companies confirms this result. Table II-3 also displays the annual average number of patent applications for the selection of companies, when we exclude the seven technology companies[8] that rely heavily on the development of electronics. Indeed, the increase in the rate of patenting between the two sub-sample periods is smaller when the technology firms are excluded. This indicates that the change in patenting primarily is a result of a surge in the rate of invention and that the patent policy change did not have a significant impact on the rate of patenting at the firms in this chapter. This finding is consistent with the notion that the surge in patenting starting in the mid-1980s was related to the technological inventions of the Information Technology era.

If the overall increase in patenting after 1984 is unrelated to the patent policy change but is correlated with a surge in the rate of technological discovery, then it is of interest to examine the patent response functions also over the full sample period. In addition to the two sub-sample periods, the chapter therefore analyzes this scenario. Of the companies in the sample that are included in the NBER patent database and can be matched to the Compustat database, 6 companies have very few patent applications and have years with no patent applications. These defense contractors have been deleted from the sample, leaving the 1969-1993 patent analysis with 39 firms when examining the full sample period. The response functions from the different sample periods are illustrated in

[8] AT&T, Computer Science Corp, Hewlett-Packard, IBM, ITT Industries, Motorola, and Texas Instruments. Not all of these companies experienced an increase in patenting. However, all seven are excluded for consistency throughout this chapter.

Figure II-11. Two lags are included in the analysis when considering a shorter than full sample period.

First consider the period from 1969-1983 before the Bayh-Dole Act had relevance for the selection of firms. Panel A of Figure II-11 illustrates how the rate of patenting increases insignificantly after an initial insignificant decrease. However, when considering the 1984-1993 period in Figure II-11, Panel B, patents start to increase right after the MPC shock, and for some lag lengths this result is significant (not shown). Similar results are seen when considering the full sample period from 1969-1993 in Figure II-11, Panel C. With the longer time-dimension in this panel, the figure displays a long-lasting significant response of patents to an MPC shock.

In Panels B and C of Figure II-11 there is some evidence that a patent shock results in MPC awards a few years after the shock. Importantly, the results from the patent analysis correspond to the results from the R&D analysis that an MPC shock leads to the development of new technology, although the evidence is strongest for the post-1984 period. The fact that both company-financed R&D and firm level patents increase in response to an MPC shock is evidence that military spending not only leads to new technology through federal funding but also results in an increase in the amount of private resources made available to discovery and innovation.

The firms in the sample that rely mainly on the development of new technology may be very important in explaining the results from the patent analysis. We therefore perform the analysis using the full time series but excluding the technology firms. The results from a bivariate PVAR with the variables PAT and MPC for the remaining firms are depicted in Figure II-12. The results are robust to leaving out the technology firms.

Additionally, Figures II-13 and II-14 display the impulse response functions from trivariate PVARs with PAT, LP, and MPC and with SP, PAT, and MPC, respectively. The results from the bivariate patent analysis remain in the trivariate systems. However, as was the case with the trivariate R&D analysis, the positive response of labor productivity to an MPC shock disappears when a technology variable is included. In addition, stock prices increase insignificantly over time after a military prime contract award. Furthermore, this chapter finds that productivity responds significantly positively to a patent shock, indicating that firms with newer technology are more productive. This result corresponds to the post-WWII findings of Christiansen (2008).

Figure II-15 depicts the results form a PVAR with R&D, PAT, and MPC included. Response functions with both two and three lags are depicted. The impulse response functions confirm the results form the bivariate analyses with R&D and patents, respectively. That is, a military prime contract award leads to the development of new technology. In Panel B of Figure II-15 (with three lags), the R&D and PAT responses to an MPC shock are insignificantly positive. However, if two lags are included, the response of PAT does become significant. Furthermore, the trivariate system supports the information inherent in the R&D and patent data: A shock to R&D leads to a significantly positive response of patent applications.

II.G. Examination of Subgroups

As evidenced in Table II-1, the military prime contractors specialize in very different areas. This section examines if the effect of a military prime contract award differs between different types of companies.

II.G.1 Oil Companies

The sample of companies includes six companies whose main business is in the oil industry. These companies may largely be affected by periods of oil crises when other businesses were facing increasing costs. It is likely that these companies are important for the results. As a robustness check, this chapter therefore performed the analysis, excluding these six companies. The resulting impulse response functions are robust to leaving out these companies, and the impulse response functions are therefore not reported.

II.G.2 Technology Firms

Although the firms in the present analysis all are large military prime contractors, several of these have a large part of their businesses outside the defense industry. Besides the oil companies as mentioned above, the sample also includes companies in the fields of technology and communication. The analysis also tried excluding these firms from the analysis. Leaving out seven technology companies[9] did not change the conclusions. Furthermore, the importance for the results of the AT&T breakup, effective 1984, has been examined by re-estimating the impulse response functions, only leaving out AT&T from the sample of companies. The overall results were robust to this change.

II.G.3 Traditional Defense Conglomerates

This chapter also tried only including the companies that are traditionally labeled as large defense conglomerates. This excludes companies with focus on subjects such as

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[9] AT&T, Computer Science Corp, Hewlett-Packard, IBM, ITT Industries, Motorola, and Texas Instruments.

oil, technology, communication, and electricity. The impulse response functions from a bivariate PVAR including only defense conglomerates in the sample[10] continue to show a positive response of labor productivity to an MPC shock. However, with the small sample size, these impulse response functions are insignificant for some lag lengths. Furthermore, for this selection of companies there is no evidence that a productivity shock leads to the award of MPCs, indicating that firm productivity is not the determining factor when MPCs are being awarded. The response of R&D to an MPC shock is very significant with this selection of companies, independently of the ordering of the two variables. In addition, patents continue to respond significantly positively.

II.G.4 Sample Length

The analysis so far has contained observations during the period between 1969 and 1993. However, the Carter-Reagan buildup did not start until the late 1970s. Therefore, this chapter tried restricting the sample period by changing the sample length. The overall results from using observations only between 1974 and 1991, between 1971 and 1988, and between 1977 and 1993 were unchanged and are therefore not reported.

II.H. Conclusion

This chapter of the dissertation has argued that military prime contracts are not awarded at the firm level based on the level of productivity at any given firm. Using data on military prime contract awards at the firm level, together with bivariate panel vector autoregressions, this chapter found evidence that firm productivity increases over time in

[10] This reduces the sample size to 22 companies.

response to a military prime contract award. This happens because of positive responses of both sales and employment with sales showing the strongest response.

Company-sponsored research and development increases after a military prime contract shock, indicating that defense contractors supplement federally funded research with own financing. Thereby, military prime contracts lead to the development of new technology. In support of this finding, the results showed that stock prices increase because of a military prime contract shock. Additionally, this fact is evidenced by the positive responses of patent applications to a military prime contract shock. Furthermore, most results remain significant when including a third variable in the panel vector autoregression.

Overall, this chapter concludes that military spending leads to the development of new technology. Thereby, positive effects on productivity can arise also at the aggregate level in the long term. If the new technologies are profitable, an implication for the neoclassical model is that the labor demand schedule is affected by military spending, leading to comovement of output, hours, and the real wage.

Acknowledgement: I thank Lone E. Christiansen for co-authoring Chapter II. As the dissertation author, I am a primary investigator and author of this chapter. I have permission from Lone E. Christiansen to use this chapter within this dissertation. A previous version of Assessing the Link between Military Spending and Productivity: Evidence from Firm-Level Data (Chapter II) appears in Lone E. Christiansen's 2007 UCSD Dissertation, titled "Essays on Productivity, Technology, and Economic Fluctuations".

II.I. Tables and Figures

Table II-1: Companies included in the Full Sample

Company Name	Primary Output: COMPUSTAT
ALLIEDSIGNAL (now Honeywell)	AIRCRAFT PARTS, AUX EQ, NEC
AMERADA HESS CORP	PETROLEUM REFINING
AMOCO CORP	PETROLEUM REFINING
AT&T	TELECOMUNICATIONS
ATLANTIC RICHFIELD CO	PETROLEUM REFINING
AUTOMATION INDUSTRIES INC	ENGR,ACC,RESH,MGMT,REL SVCS
BENDIX CORP	MOTOR VEHICLE PART,ACCESSORY
BOEING CO	AIRCRAFT
CHEVRON CORP	PETROLEUM REFINING
COMPUTER SCIENCES CORP	CMP PROGRAMMING,DATA PROCESS
EATON CORP	MOTOR VEHICLE PART,ACCESSORY
EMERSON ELECTRIC CO	ELECTR, OTH ELEC EQ, EX CMP
E-SYSTEMS INC	SRCH,DET,NAV,GUID,AERO SYS
EXXON MOBIL CORP	PETROLEUM REFINING
FMC CORP	CHEMICALS & ALLIED PRODS
FORD MOTOR CO	MOTOR VEHICLES & CAR BODIES
GENCORP INC	GUIDED MISSILES & SPACE VEHC
GENERAL DYNAMICS CORP	SHIP & BOAT BLDG & REPAIRING
GENERAL ELECTRIC CO	CONGLOMERATES
GENERAL MOTORS CORP	MOTOR VEHICLES & CAR BODIES
GRUMMAN CORP	AIRCRAFT
GTE CORP	PHONE COMM EX RADIOTELEPHONE
HARRIS CORP	SRCH,DET,NAV,GUID,AERO SYS
HERCULES INC	MISC CHEMICAL PRODUCTS

Note: This table is continued on the next page.

Table II-1 (continued): Companies included in the Full Sample, continued from previous page

Company Name	**Primary Output: COMPUSTAT**
HEWLETT-PACKARD CO	COMPUTER & OFFICE EQUIPMENT
HONEYWELL INC (pre 1999)	AUTOMATIC REGULATNG CONTROLS
INTL BUSINESS MACHINES CORP	CMP PROGRAMMING,DATA PROCESS
ITT INDUSTRIES INC	PUMPS AND PUMPING EQUIPMENT
LEAR SIEGLER INC	SRCH,DET,NAV,GUID,AERO SYS
LITTON INDUSTRIES INC	SHIP & BOAT BLDG & REPAIRING
LOCKHEED MARTIN CORP	GUIDED MISSILES & SPACE VEHC
LORAL CORP	SRCH,DET,NAV,GUID,AERO SYS
LTV CORP	STEEL WORKS & BLAST FURNACES
MARTIN MARIETTA CORP	GUIDED MISSILES & SPACE VEHC
MCDONNELL DOUGLAS CORP	AIRCRAFT
MOBIL CORP	PETROLEUM REFINING
MOTOROLA INC	RADIO,TV BROADCAST, COMM EQ
NORTHROP GRUMMAN CORP	SRCH,DET,NAV,GUID,AERO SYS
RAYTHEON CO	SRCH,DET,NAV,GUID,AERO SYS
ROCKWELL AUTOMATION	ELECTRICAL INDL APPARATUS
TEXAS INSTRUMENTS INC	SEMICONDUCTOR,RELATED DEVICE
TEXTRON INC	AIRCRAFT
TODD SHIPYARDS CORP	SHIP & BOAT BLDG & REPAIRING
TRW INC	MOTOR VEHICLE PART,ACCESSORY
UNITED TECHNOLOGIES CORP	AIRCRAFT AND PARTS

Table II-2: Competitiveness of Military Prime Contract Awards, 1998-2003

Panel A. Type of Contracts Awarded, %

	Fixed Price	**Cost-Plus**	**Time and Materials**	**Other**	**No Information**
Lockheed Martin	46.77	49.68	2.43	0.91	0.21
Boeing	70.25	27.42	2.08	0.19	0.06
Raytheon Co	57.94	37.53	2.98	1.21	0.35
Northrop Grumman	49.55	42.48	2.13	2.18	3.66
General Dynamics	60.02	38.87	0.44	0.44	0.24
United Technologies	77.25	22.14	0.36	0.25	0
General Electric	87.82	10.46	0.34	0.45	0.93
TRW Inc	23.24	70.86	2.45	0.44	3.01
Honeywell Inc-AlliedSignal	72.44	21.52	2.69	3.02	0.34
Textron	47.77	50.97	0.91	0.27	0.08
Litton	55.96	35.73	2.11	1.62	4.58
IBM	42.42	8.6	12.33	3.31	33.34
GTE Corporation	61.36	33.04	3.21	1.3	1.09

Source: Center for Public Integrity, “Outsourcing the Pentagon”.

Table II-2 (continued): Competition of Military Prime Contract Awards, 1998-2003

Panel B. Competition: How Contractors Won the Contracts, %
B1. Competition categories

	Full and Open	Not Full and Open	Set-Aside	Architect -Engr	Other	No Information
Lockheed Martin	24.95	74.11	0.03	0.00	0.56	0.35
Boeing	39.91	59.55	0.01	0.05	0.34	0.14
Raytheon Co	31.19	66.52	0.02	0.01	1.38	0.88
Northrop Grumman	33.31	59.03	0.08	0.01	1.5	6.07
General Dynamics	30.1	69.21	0.02	0.01	0.29	0.38
United Technologies	2.67	95.28	0	0	1.69	0.36
General Electric	8.77	88.44	0.17		1.09	1.53
TRW Inc	70.37	24.44	0.02	0	1.85	3.33
Honeywell Inc-AlliedSignal	30.62	62.5	0.02	0.02	4.08	2.77
Textron	4.67	94.62	0.05		0.36	0.3
Litton	37.7	55.53	0.02		1.18	5.57
IBM	34.86	15.5			2.06	47.57
GTE Corporation	70.72	21.35	0.2		5.37	2.37

Full and open competition generally indicates that the contracts went out to competitive bid. **Not full and open** generally don't go out to bid. **Set-aside** contracts are competitive, but only certified small businesses can bid on them. Most of the contracts with **no information** were awarded on the "federal schedule." Contractors pre-qualify to supply specific goods and services, and federal employees can order them without going through the bidding process.
Source: Center for Public Integrity, “Outsourcing the Pentagon”.

Table II-2 (continued): Competition of Military Prime Contract Awards, 1998-2003

Panel B (continued). Competition: How Contractors Won the Contracts
B2. Number of Bidders in Contracts Won with Full and Open Competition, %

	One	Two	Three to Five	Six to Ten	Eleven or More
Lockheed Martin	8.20	54.81	24.17	11.63	1.18
Boeing	6.74	77.63	11.89	2.90	0.84
Raytheon Co	10.95	37.78	34.96	13.59	2.72
Northrop Grumman	10.45	65.63	17.42	5.32	1.19
General Dynamics	9.93	40.54	31.77	7.81	9.95
United Technologies	21.2	27.89	45.23	2.78	2.9
General Electric	14.61	34.16	30.48	11.3	9.45
TRW Inc	4.26	57.32	25.15	12.92	0.36
Honeywell Inc-AlliedSignal	16.96	30.53	37.19	14.82	0.51
Textron	20.94	58.36	11.55	6.33	2.81
Litton	5.89	82.81	7.49	3.76	0.04
IBM	33.47	14.19	30.6	5.41	16.33
GTE Corporation	25.52	65.55	6.71	1.09	1.12

Source: Center for Public Integrity.

Table II-2 (continued): Competition of Military Prime Contract Awards, 1998-2003

Panel B (continued). Competition: How Contractors Won the Contracts
B3. Reasons for Contract Awards with Less than Full and Open Competition, %

	Sole Source	National security	International agreement	Urgency	Public interest	Authorized by statute	Other
Lockheed Martin	79.01	3.65	12.26	4.95	0.00	0.10	0.03
Boeing	89.49	0.51	7.55	2.38	0.00	0.05	0.02
Raytheon Co	79.46	7.17	4.5	5.22	1.67	1.46	0.52
Northrop Grumman	83.16	0.83	3.57	4.09		0.22	8.12
General Dynamics	40.49	0.38	1.31	3.35	2.14	11.16	41.17
United Technologies	92.39		4.18	3.23		0.09	0.17
General Electric	95.36	0.28	0.57	3.49	0.18	0.02	0.1
TRW Inc	58.73	0.98	27.84	12.36		0.09	0.01
Honeywell Inc-AlliedSignal	93.42	0	0.96	4.85		0.09	0.67
Textron	90.80	1.37	3.59	4.22	0	0.01	0.02
Litton	37.10	0.59	0.25	0.47		0.29	61.31
IBM	96.36		1.18	1.77		0.69	

Contracts "authorized by statute" were approved by Congress, generally as provisions giving preference to minority-owned businesses and the like.
Source: Center for Public Integrity.
http://www.publicintegrity.org/pns/

Note: Some companies enter with different names in the table above compared to the firms in the sample used for the analysis. This is a result of company mergers during the 1990s.

Table II-3: Average Annual Number of Patents for a Selection of Firms

Company Name	1969-1983	1984-1993	1969-1993
ALLIEDSIGNAL (now Honeywell)	150.6	254.6	192.2
AMERADA HESS CORP	0.1	0.5	0.3
AMOCO CORP	100.9	139.6	116.4
AT&T CORP	491.1	446.6	473.3
ATLANTIC RICHFIELD CO	86.3	104.6	93.6
AUTOMATION INDUSTRIES INC	9.4		
BENDIX CORP	151.5		
BOEING CO	93.1	146.6	114.5
CHEVRON CORP	213.1	85.9	162.2
EATON CORP	106.1	131.7	116.3
EMERSON ELECTRIC CO	67.3	81.1	72.8
E-SYSTEMS INC	10.5	10.4	10.5
EXXON MOBIL CORP	249.8	232.5	242.9
FMC CORP	124.3	75.2	104.7
FORD MOTOR CO	168.7	236.1	195.7
GENCORP INC	44.6	22.0	35.6
GENERAL DYNAMICS CORP	34.5	29.9	32.6
GENERAL ELECTRIC CO	821.9	855.9	835.5
GENERAL MOTORS CORP	491.9	691.0	571.6
GRUMMAN CORP	14.4	48.9	28.2
GTE CORP	221.3	199.9	212.7
HARRIS CORP	44.5	64.7	52.6
HERCULES INC	52.5	43.0	48.7
HEWLETT-PACKARD CO	54.3	268.2	139.8
HONEYWELL INC (pre 1999)	183.4	183.8	183.6

Note: All Companies Excl. Tech is an average over all companies in the sample, excluding the following: AT&T, Computer Science Corp, Hewlett-Packard, IBM, ITT Industries, Motorola, and Texas Instruments. This table is continued on the next page.

Table II-3 (continued): Average Annual Number of Patents for a Selection of Firms

Company Name	1969-1983	1984-1993	1969-1993
INTL BUSINESS MACHINES CORP	517.3	824.1	640.0
ITT INDUSTRIES INC	34.9	10.8	25.2
LEAR SIEGLER INC	21.9	9.3	19.8
LITTON INDUSTRIES INC	52.7	62.6	56.6
LOCKHEED MARTIN CORP	31.5	30.1	30.9
LORAL CORP	1.3	12.3	5.7
LTV CORP	8.9	8.5	8.8
MARTIN MARIETTA CORP	15.9	38.3	24.9
MCDONNELL DOUGLAS CORP	43.1	32.5	38.8
MOBIL CORP	242.1	307.2	278.3
MOTOROLA INC	197.5	549.7	338.4
NORTHROP GRUMMAN CORP	15.5	24.4	19.1
RAYTHEON CO	82.8	70.9	78.0
ROCKWELL AUTOMATION	177.7	128.1	157.8
TEXAS INSTRUMENTS INC	166.5	339.2	235.6
TEXTRON INC	73.5	34.7	58.0
TRW INC	89.3	85.2	87.6
UNITED TECHNOLOGIES CORP	171.4	264.3	208.6
ALL COMPANIES	138.0	178.1	153.6
ALL COMPANIES EXCL. TECH	120.4	138.2	168.2

Note: All Companies Excl. Tech is an average over all companies in the sample, excluding the following: AT&T, Computer Science Corp, Hewlett-Packard, IBM, ITT Industries, Motorola, and Texas Instruments.

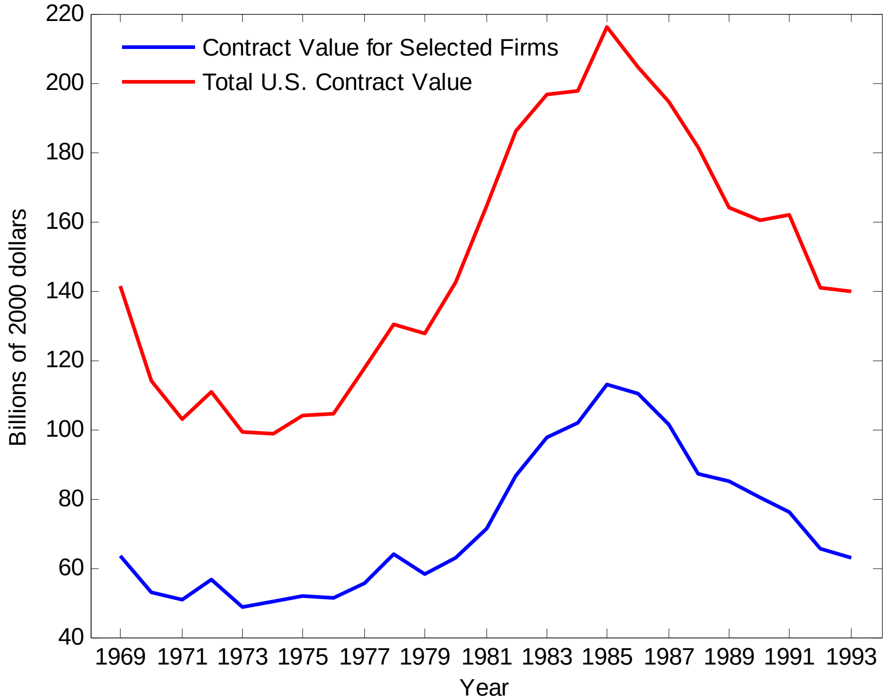


Figure II-1: Aggregate Military Prime Contract Awards

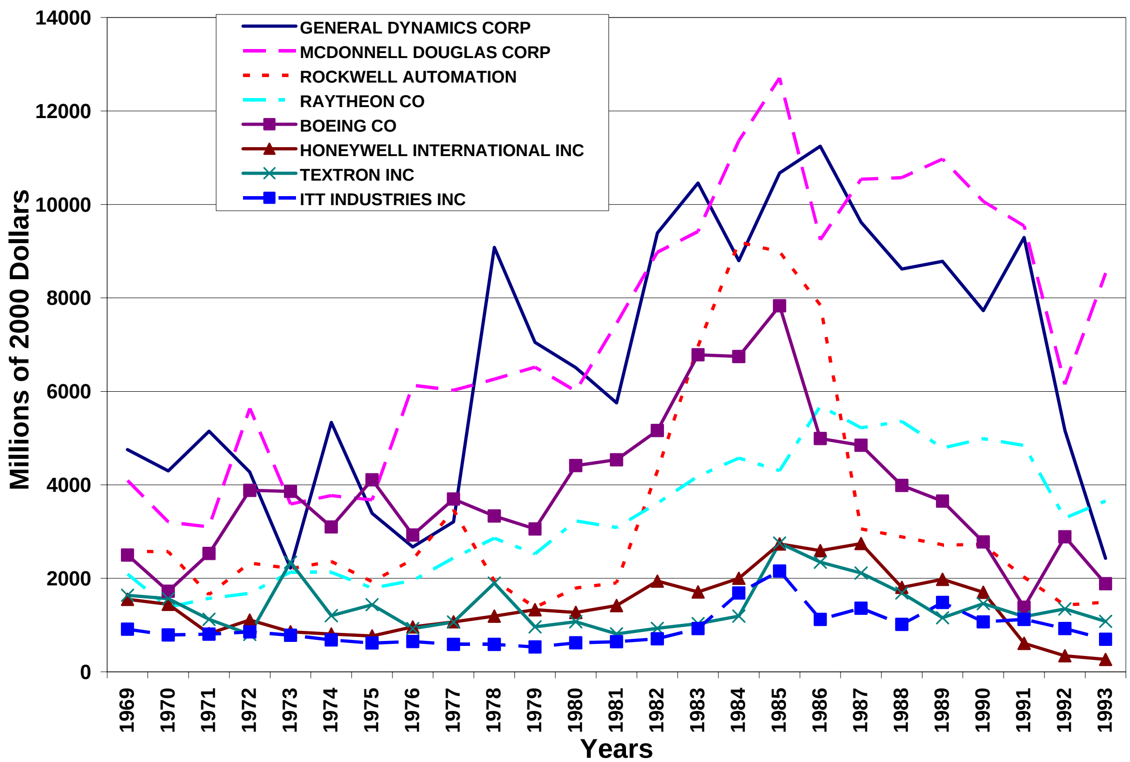
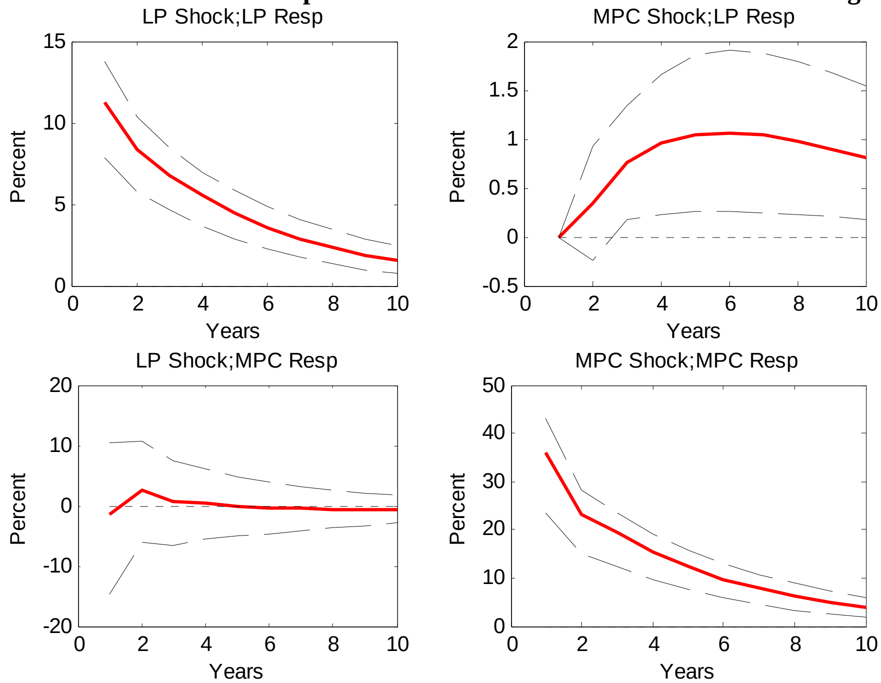
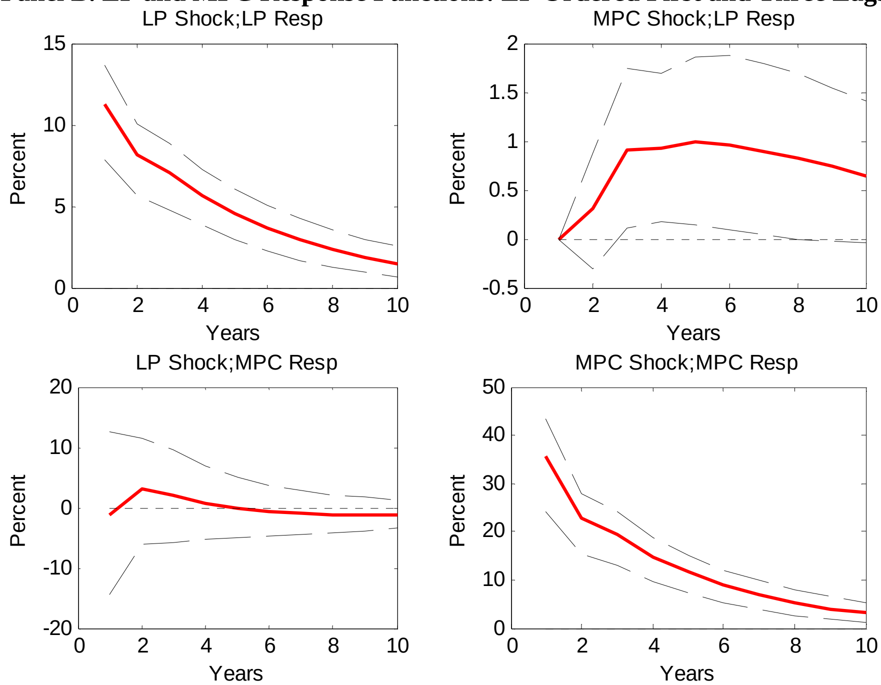


Figure II-2: Firm-Level Real Military Prime Contracts

Panel A. LP and MPC Response Functions: LP Ordered First and Two Lags



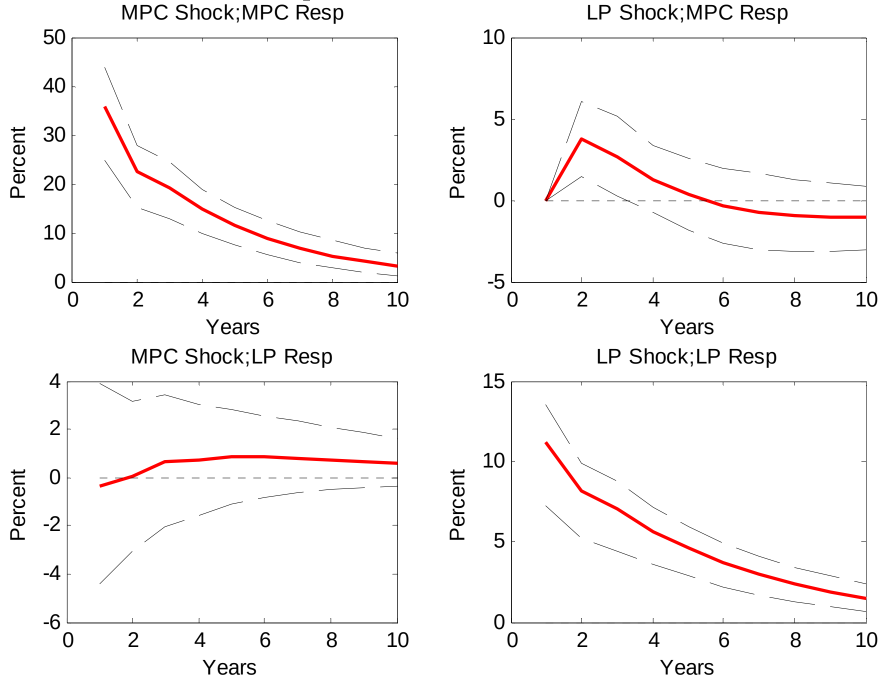
Panel B. LP and MPC Response Functions: LP Ordered First and Three Lags



Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. Year 1 is the time of the shock.

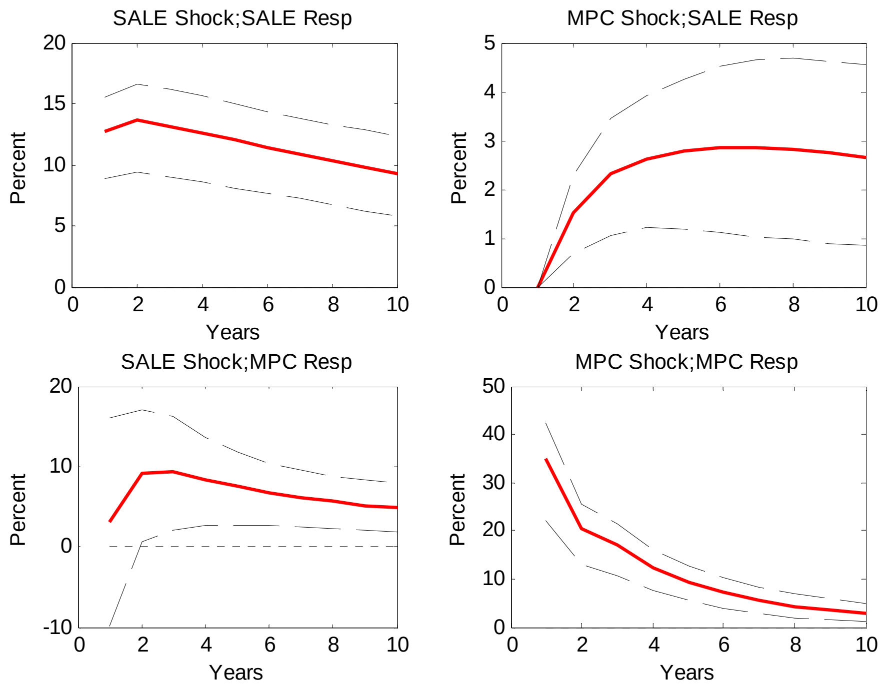
Figure II-3: Bivariate PVAR with LP and MPC

Panel C. LP and MPC Response Functions: MPC Ordered First and Three Lags



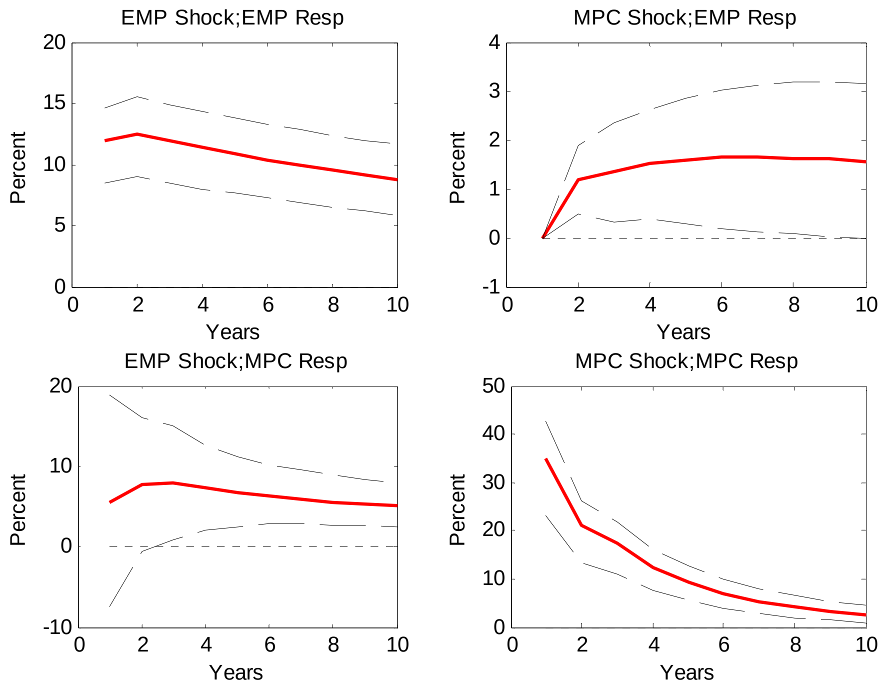
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 45 firms are included.

Figure II-3 (continued): Bivariate PVAR with LP and MPC



Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals.3 lags are included.

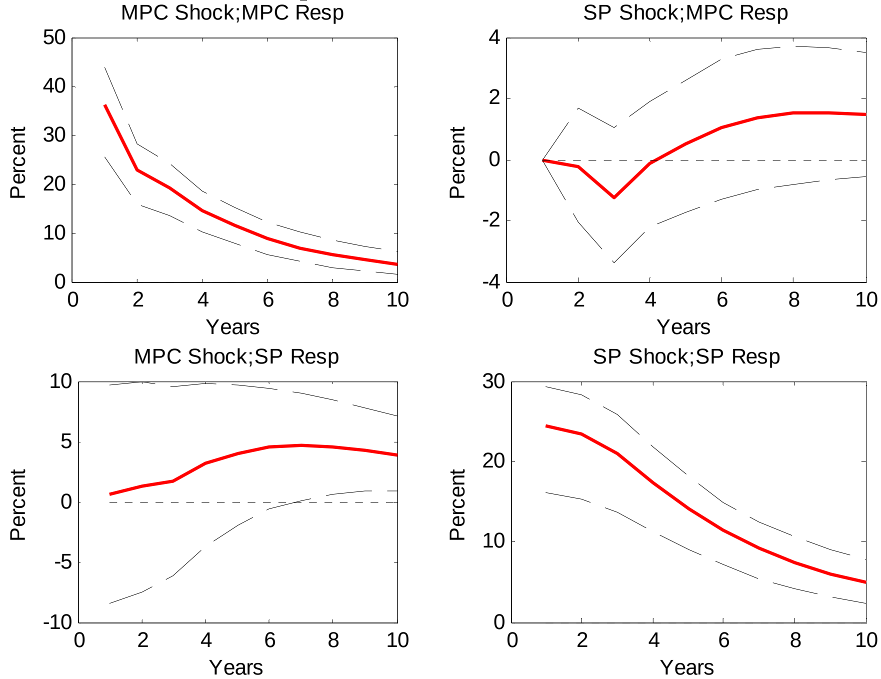
Figure II-4: Bivariate PVAR with SALE and MPC



Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 3 lags are included.

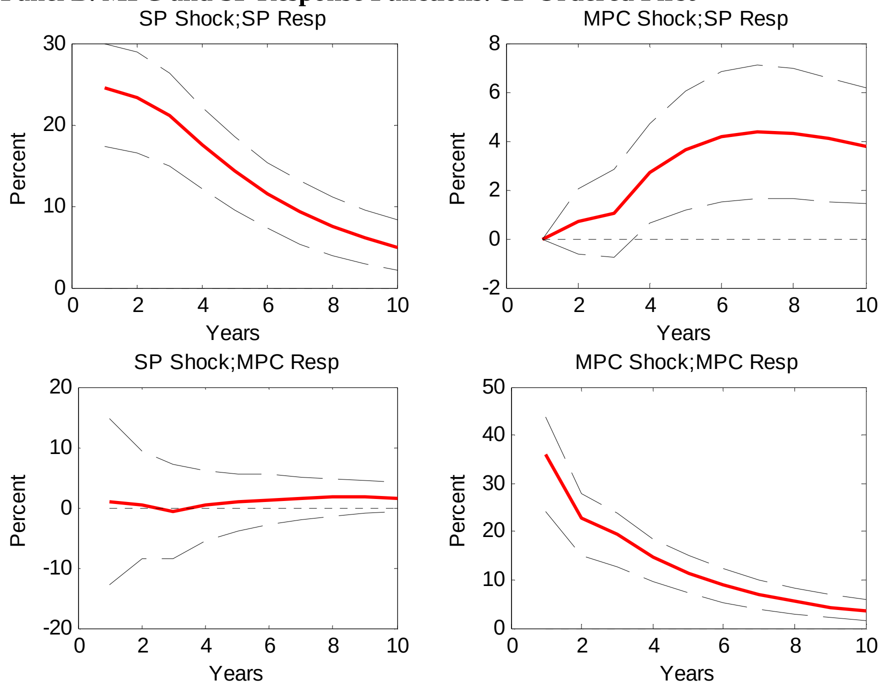
Figure II-5: Bivariate PVAR with EMP and MPC

Panel A. MPC and SP Response Functions: MPC Ordered First



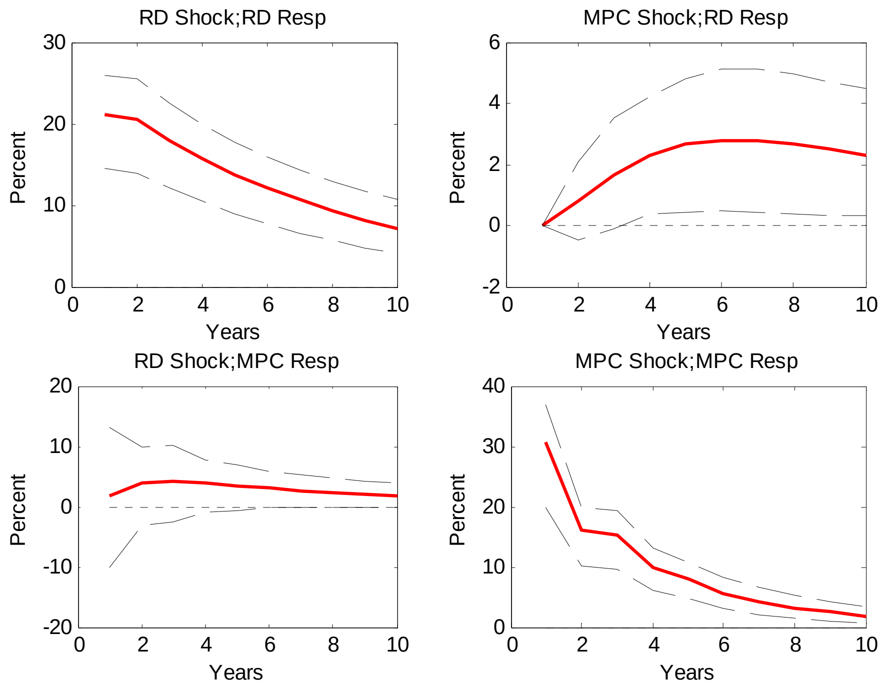
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 3 lags are included.

Panel B. MPC and SP Response Functions: SP Ordered First



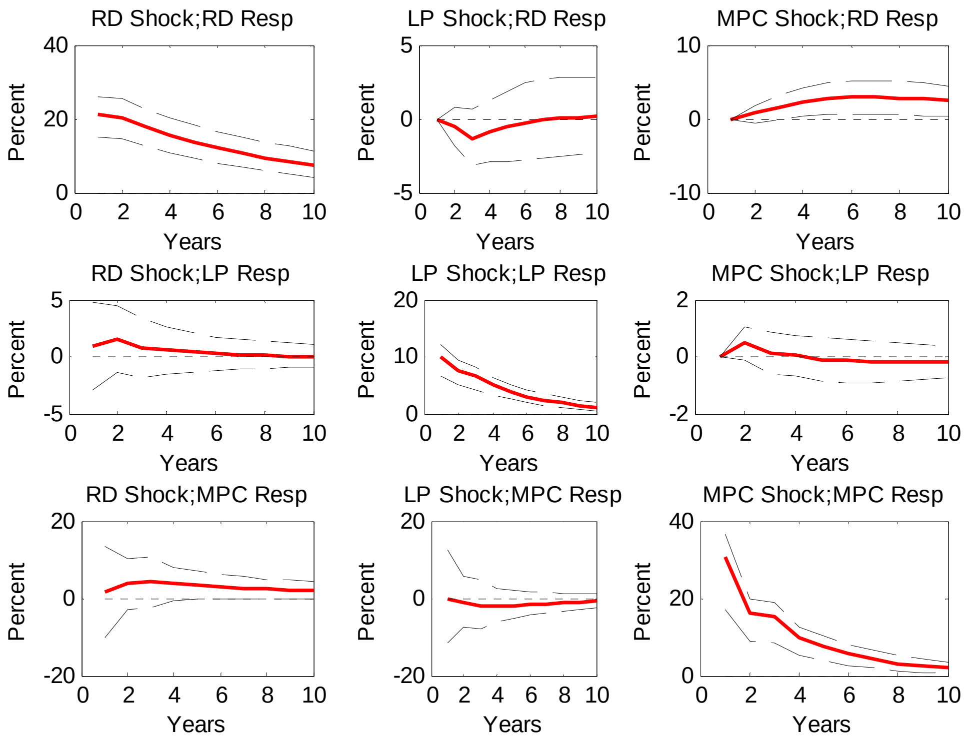
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 3 lags are included.

Figure II-6: Bivariate PVAR with SP and MPC



Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 43 firms are included. 3 lags are included.

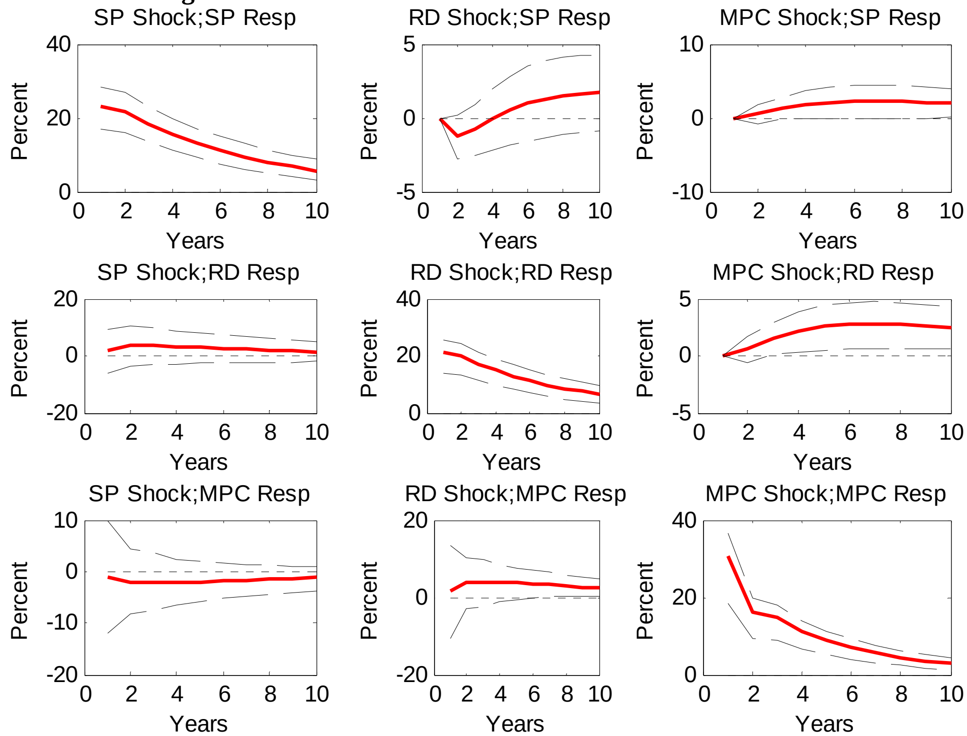
Figure II-7: Bivariate PVAR with RD and MPC



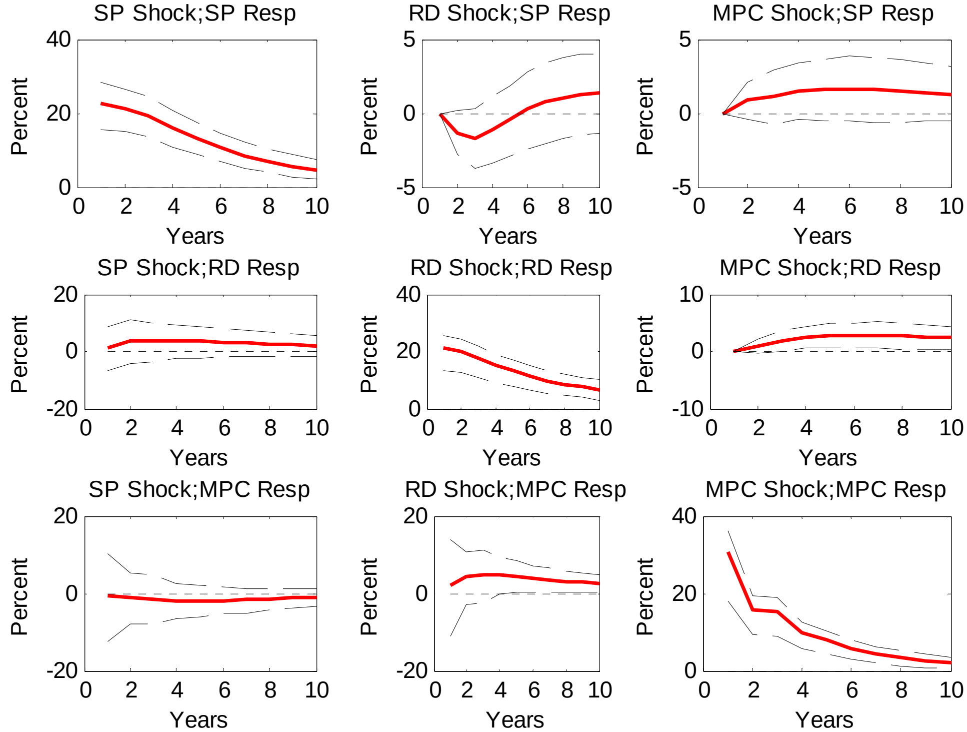
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 3 lags are included.

Figure II-8: Trivariate PVAR with RD, LP, and MPC

Panel A. Two lags



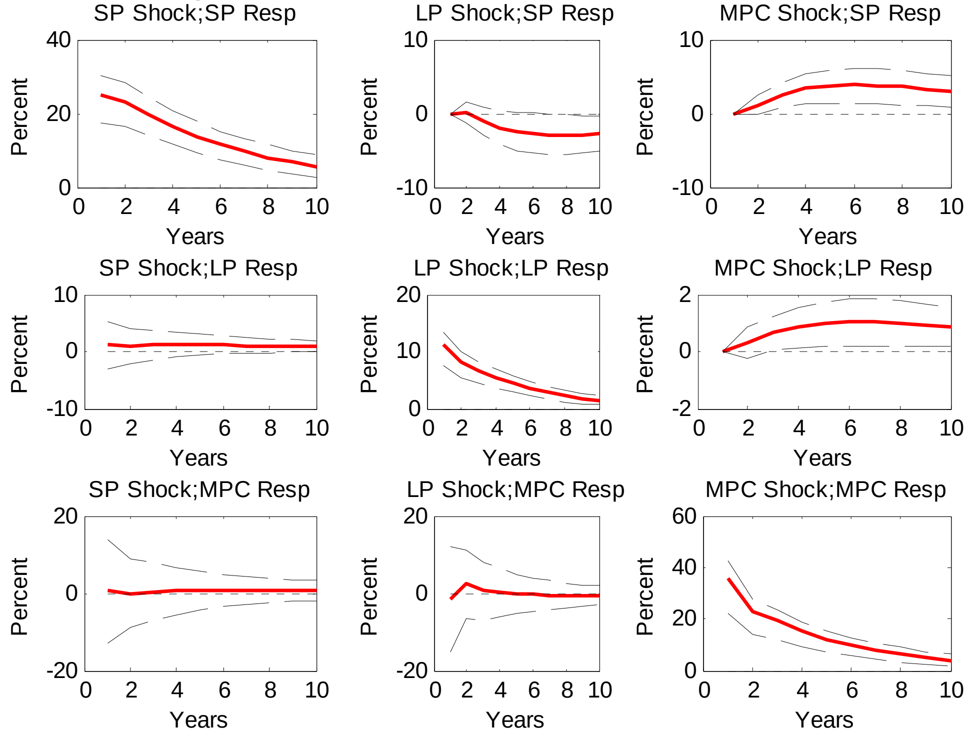
Panel B. Three Lags



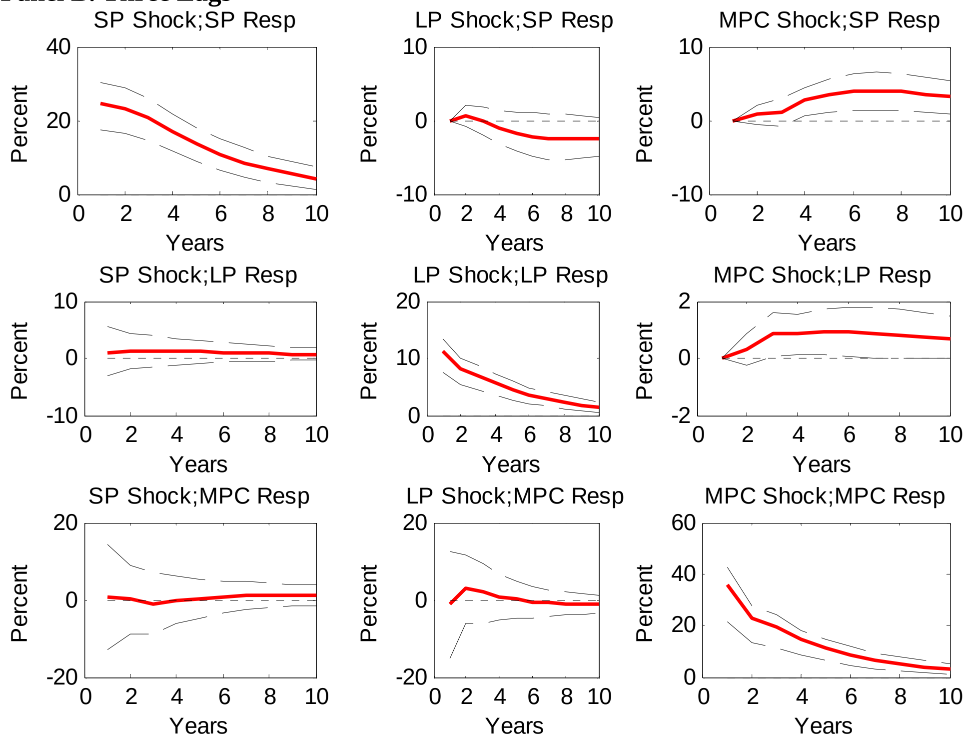
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals.

Figure II-9: Trivariate PVAR with SP, RD, and MPC

Panel A. Two Lags



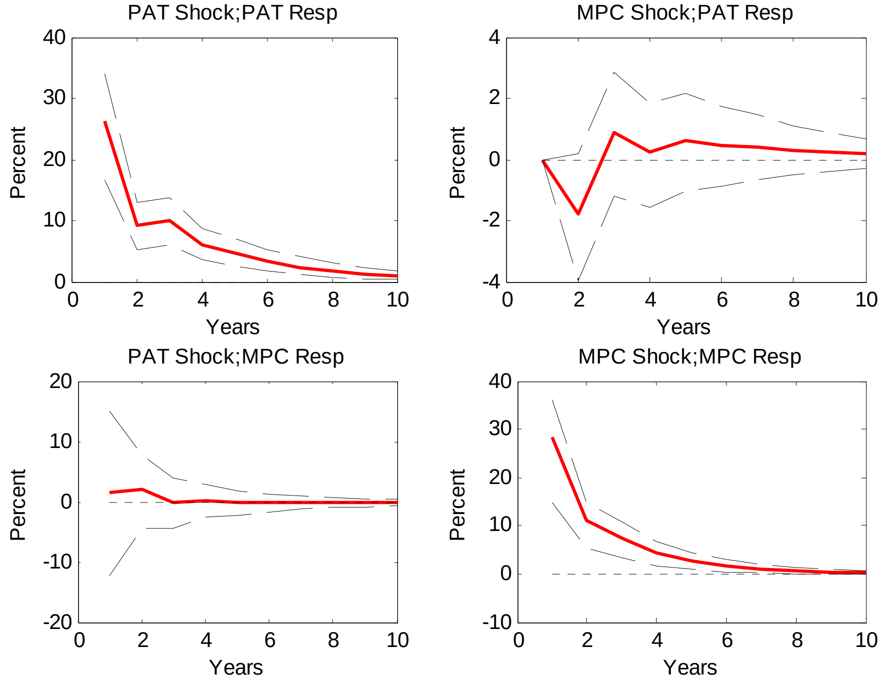
Panel B. Three Lags



Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals.

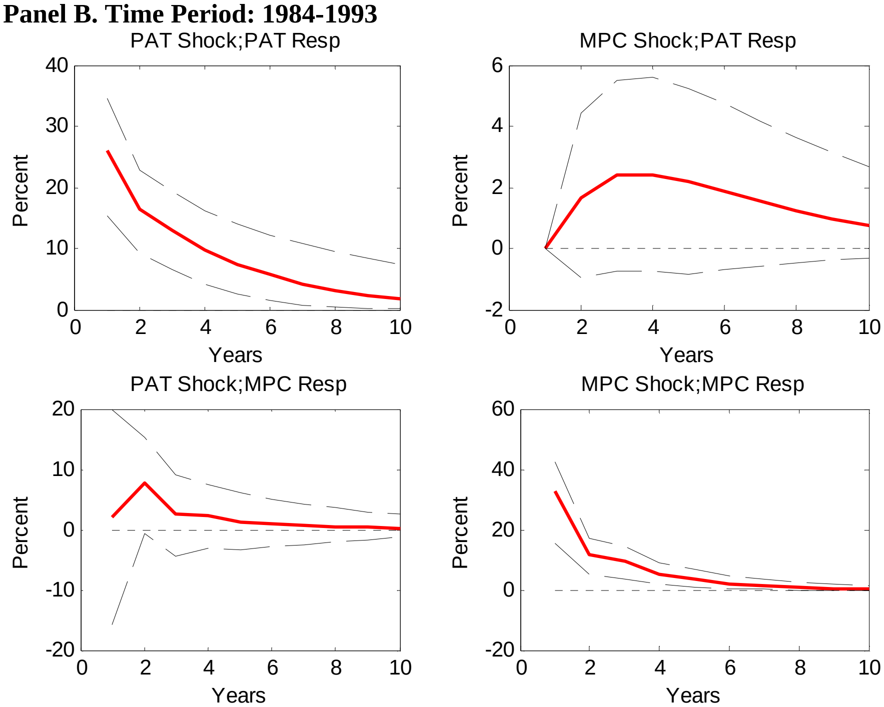
Figure II-10: Trivariate PVAR with SP, LP, and MPC

Panel A. Time Period: 1969-1983



Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 2 lags are included.

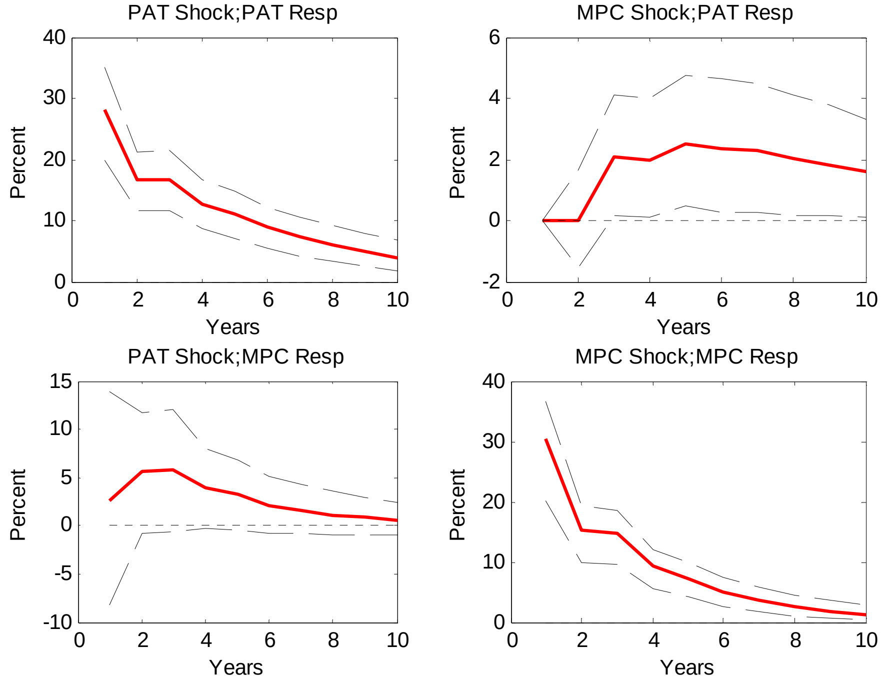
Panel B. Time Period: 1984-1993



Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 2 lags are included.

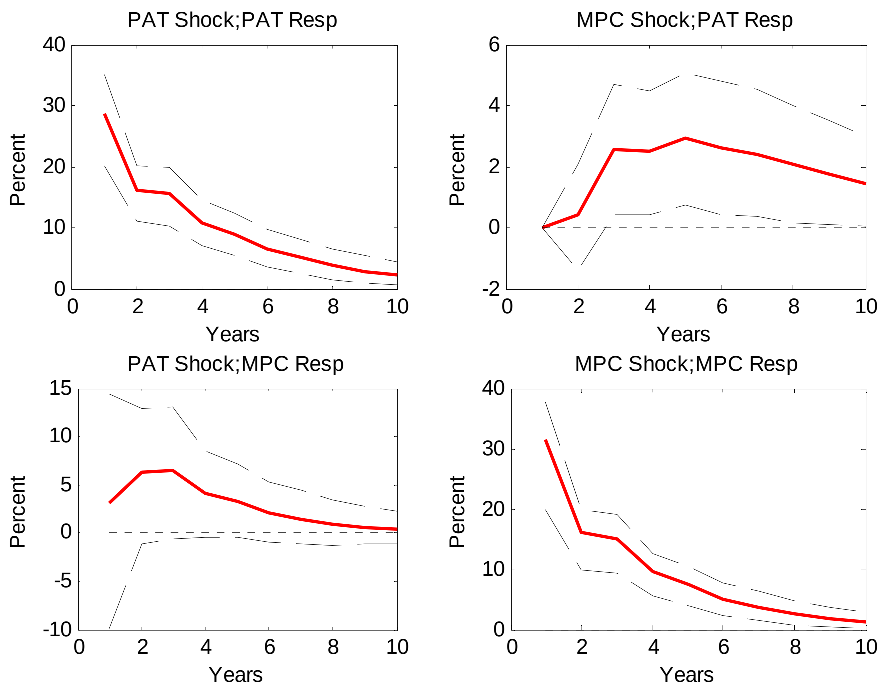
Figure II-11: Bivariate PVAR with PAT and MPC

Panel C. Time Period: 1969-1993



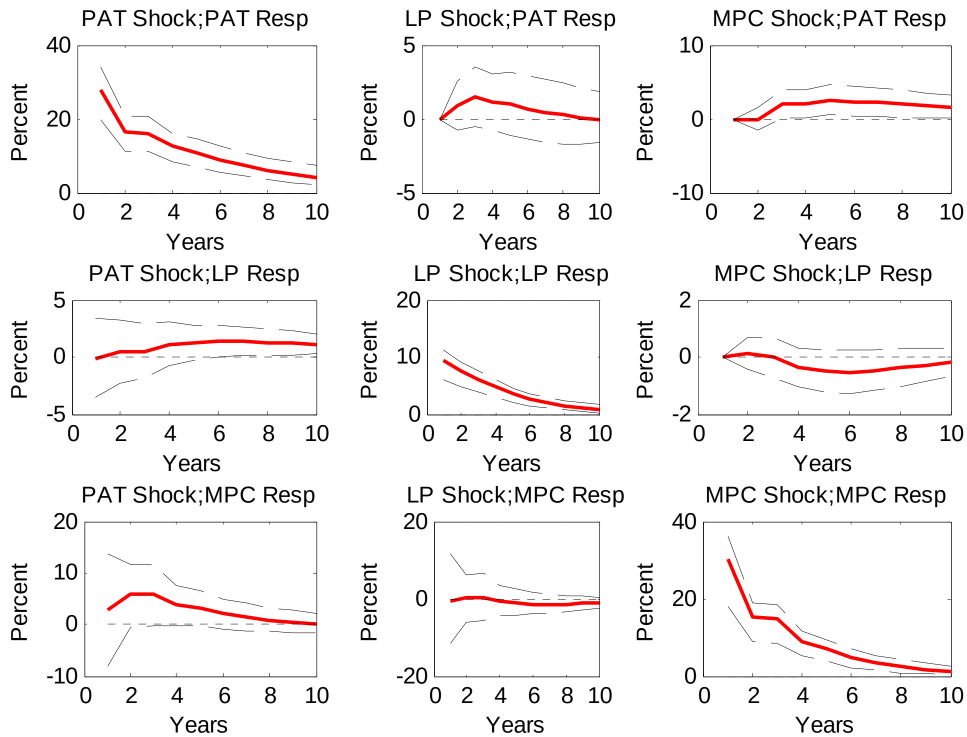
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 39 firms are included. 3 lags are included.

Figure II-11 (continued): Bivariate PVAR with PAT and MPC



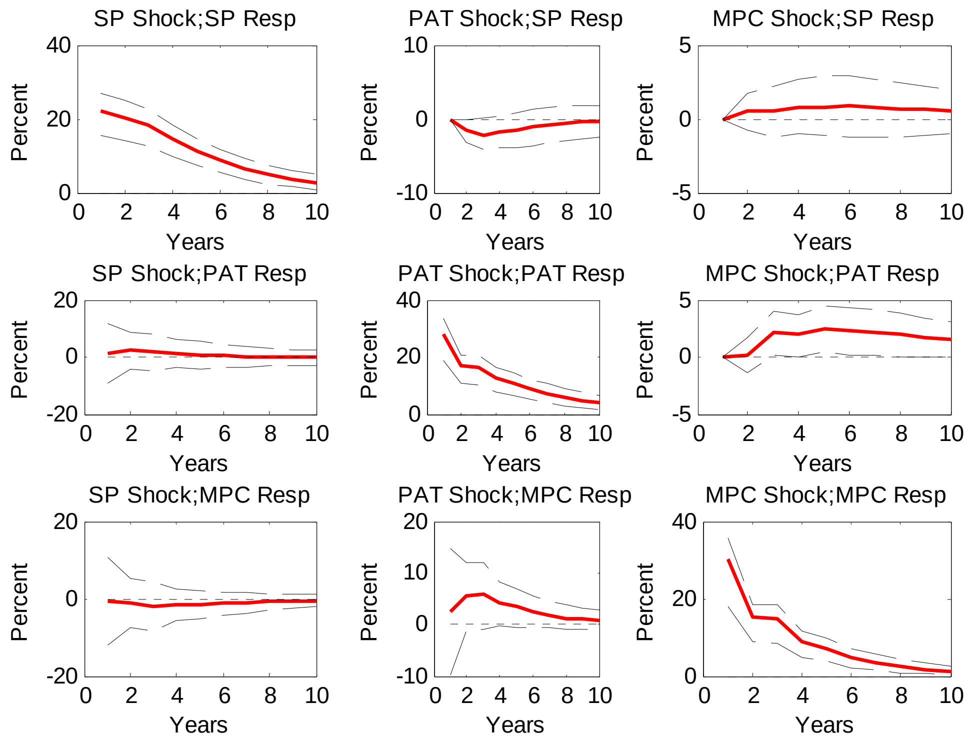
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 34 firms included. 3 lags are included. Technology firms not included in the sample.

Figure II-12: Bivariate PVAR with PAT and MPC, 1969-1993. Excluding the Technology Firms



Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 39 firms are included. 3 lags are included.

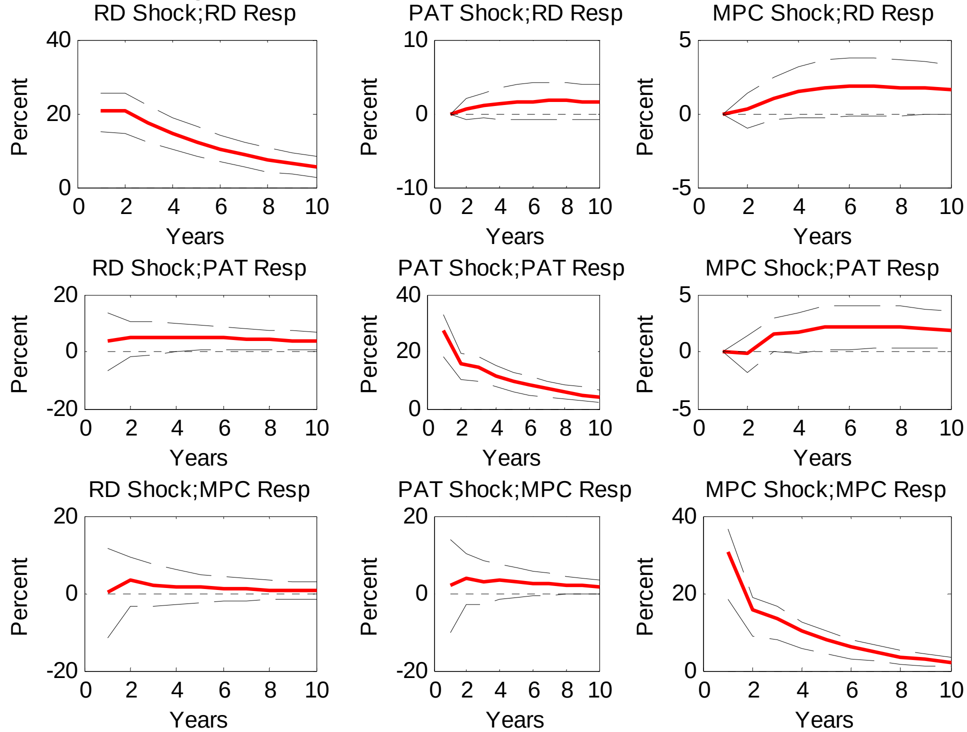
Figure II-13: Trivariate PVAR with PAT, LP, and MPC, 1969-1993



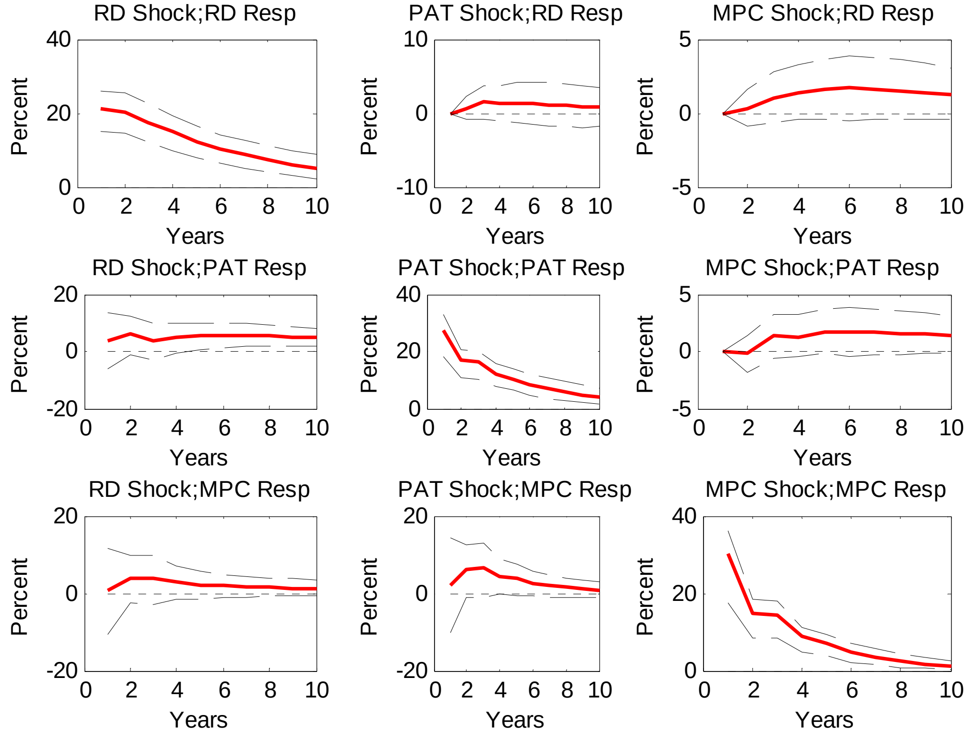
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 3 lags are included.

Figure II-14: Trivariate PVAR with SP, PAT, and MPC, 1969-1993

Panel A. Two Lags



Panel B. Three Lags



Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals.

Figure II-15: Trivariate PVAR with RD, PAT, and MPC, 1969-1993

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Chapter III

Defense Spending, Productivity, and Technological Change: A Regional Approach

Abstract

Do changes in military spending stimulate regional technological progress and local labor productivity? Military prime contract data together with Gross Domestic Product by state, regional employment, and state-level patent statistics are used to explore this question. Through panel vector autoregressions with the 50 states and the District of Columbia, this chapter of the dissertation finds that output and employment increase following a military spending shock, but that labor productivity only increases insignificantly. Results from the patent data show that military spending leads to the development of new technology. However, the 50 states and the district are not all affected similarly. States with relatively few military prime contract dollars per person tend to be more positively affected than traditionally large military states.

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III.A. Introduction

During the post-WWII period, military spending has experienced large and persistent fluctuations with buildups during the Korean War, the Vietnam War, the Carter-Reagan period, and most recently after September 11, 2001 and during the Iraqi War. The recent buildup has created renewed interest in examining the economic effects of defense spending. Since aggregate economic findings occur together with variations at the regional level, this chapter of the dissertation explores the effect of defense spending while accounting for regional differences in the demand for defense products.

Indeed, there are real differences in the amount of military spending across the U.S. states. In particular, at the peak of the Carter-Reagan military buildup, California received $27.7 billion in military prime contracts (MPCs) or 4.8% of California GDP, while Delaware received only $224 million, accounting for 1.6% of Delaware GDP. Moreover, even when taking into account population, California continues to outperform most states when considering the dollar amount received because of military prime contracting. These spatial differences are important to take into consideration when exploring the effects of military spending.

This chapter examines the economic consequences of MPCs for labor productivity and the development of new technology at the U.S. regional level. Data on Gross Domestic Product by State (GDPS) and regional employment are used in calculating labor productivity data at the state level. Furthermore, patent data from the National Bureau of Economic Research (NBER) patent database can be sorted by the state of the first inventor, making it possible to perform an empirical and statistical analysis of the regional effects of military spending and of how MPCs may lead to the development of new technology.

The time dimension in this chapter is limited to focus on the years around and during the Carter-Reagan military buildup. The event is of great interest as military spending was driven by factors unrelated to U.S. economic conditions. In fact, it was initiated after the Soviet invasion of Afghanistan at the end of 1979. The invasion started a burst of military related expenditure that peaked in 1986. During the seven year buildup government consumption on national defense increased from 5.7% to 7.4% of GDP. For further details see Ramey and Shapiro (1998) who provide a thorough description of the event.

Through the use of panel vector autoregressions this chapter finds that a typical state experiences an increase in GDPS and employment with only insignificant effects on labor productivity. Interestingly, however, the number of patents increase following a MPC shock, indicating that new technology is being developed because of the military spending. In addition, the chapter finds that states respond differently depending on the importance of the defense sector in the given state. Areas that generally receive few prime contracts respond positively to an increase in contract awards while large military states are less significantly affected.

In the following section, Chapter III briefly reviews the related literature on the U.S. and state levels of aggregation. Section III.C. describes the data in detail and explores the differences in military spending across the 50 states and the District of Columbia. Section III.D. describes the panel vector autoregression that is used to compute the empirical results, which are presented in Section III.E. Section III.F.

examines subgroups of individual states in order to explore how historically small and large military states may respond differently to an increase in MPCs. Section III.G. concludes.

III.B. Related Literature

Spatial studies have examined the effects of military spending on regional economic activity. Given data limitations, these papers have mainly relied on employment and personal income data. Of these, Mehay and Solnick (1990) and Hooker and Knetter (1997) find positive effects on regional employment after an increase in military spending, and Hooker and Knetter argue for the exogeneity of MPCs to regional economic activity. Markusen, Hall, Campbell, and Deitrick (1991) and Crump (1989) explore the spatial distribution of military expenditures in the United States.

Other papers of interest include Blanchard and Katz (1992) and Davis, Loungani, and Mahidhara (1997). Blanchard and Katz examine how U.S. states have adjusted after being affected by an adverse shock to employment and examine the effect on wages. Davis, Loungani, and Mahidhara (1997) examine how various driving forces are affecting movements in employment growth and unemployment rates. They consider changes in military expenditures and fluctuations in the price of oil and find that employment falls and the unemployment rate increases in response to a fall in military expenditures. Corresponding to the findings of Blanchard and Katz (1992), they conclude that migration of workers between states helps dampen the effect on state unemployment rates after regional shocks. Additionally, Cullen and Fishback (2006) examine the implications of government spending for local economic activity during World War II. They find that World War II spending did not affect consumption growth rates.

At the macroeconomic level, some existing literature has tried to examine the effects of military spending on productivity. However, various conclusions have been reached. Edelberg, Eichenbaum, and Fisher (1999) and Ramey and Shapiro (1998) find that wages and labor productivity may decrease following a military buildup. On the contrary, Rotemberg and Woodford (1992) find evidence of positive effects on the real wage. More evidence is therefore needed within this area of research.

This chapter examines the effect of military spending on regional average labor productivity. As the existing literature has found conflicting evidence on the response of productivity to government expenditures, this analysis can provide important insight on this topic. In addition, by estimating a panel vector autoregression this chapter is able to take into account the dynamic interactions between the economic variables across time. See also Chapter II of this dissertation for a corresponding analysis using firm-level data on large military prime contractors.

On the subject of technological development, Acs, Anselin, and Varga (2002) have examined patent counts at the regional level in order to measure the production of knowledge. They also argue for the validity of patent counts as a measure of innovative activity. Indeed, they compare the regional innovation output indicator developed by the U.S. Small Business Administration to regional patent data from the United States Patent and Trademark Office (USPTO) and find that patents and the innovation indicator provide similar results. Their findings therefore support the use of patent counts in studies examining technological change.

III.C. Data

The MPC data are from the Department of Defense Statistical Information Analysis Division. These data give information about the dollar value of prime contracts[1] awarded to businesses, federal agencies, and non-profit and educational institutions in the 50 states and the District of Columbia in fiscal years from 1962 to 2006. These contracts cover a variety of products and are not limited to combatant aircraft. Examples of products include rechargeable batteries, packing equipment, footwear, food services, jet engines, pharmaceutical drugs, and software.[2] When an action report is filed for a contract, the prime contractor assigns the fiscal obligation to the region that is allocated the largest dollar portion of the contract. This region is referred to as the contract's principal place of performance. Using this information, the contracts were sorted at the state level. This reveals how states differ in the level of annual contract dollars received. Indeed, some states receive on average contracts of more than $5 billion annually, while other states have contracts of less than $100 million on average.[3]

It should be mentioned that the MPC data do not take into account subcontracting outside the principal place of performance. Therefore, MPC data at the state level as used in this chapter may over- or underestimate the actual expenditure level in a given state.

[1] The MPC data are Department of Defense Form 350 individual contract action reports in excess of $25,000. Contracts in excess of $10,000 were reported prior to 1983. However, these contracts make up a very small fraction of the total. Therefore, following Hooker and Knetter (1997), the time inconsistent censoring point is ignored.

[2] Other examples include missile components, underwater sound equipment, trash collection, architect services, highway maintenance, hotel services, ammunition, data analysis, tires, office space, and air conditioning equipment.

[3] In the State of Montana, the years 1974 and 1975 enter in the original data with a negative contract value. According to the Department of Defense no state should have a year with negative contracts. The raw data indicates a cancelled contract for the firm Kiewit Morrison Fischbach. However, the positive corresponding value does not enter in these years. This indicates a misreporting in the data. This chapter therefore used linear interpolation for these two years to estimate the actual contract value. As a robustness check, the analysis also tried excluding Montana from the estimations. This did not affect the overall results.

As such, this is a potential source of measurement error. When included in this study, MPC dollar values per state have been converted into real terms by deflating with the GDP deflator, and the natural logarithm was then taken of the series.

Table III-1 contains the average real dollar values of state-level MPCs in millions of dollars, and Figure III-1 plots these numbers in a map after normalizing with state population. In Figure III-1, the lightest colored states receive the highest amount of contracting dollars per state resident. In particular, California, Washington, and Missouri each receive over $747 of contracts per person whereas states such as Arkansas, South Carolina, and Oregon have less than $364 military contracting dollars per resident.

Figure III-2 uses MPC time series data, aggregated to the eight Bureau of Economic Analysis areas[4], to confirm that there are substantial differences in the level of MPCs across the U.S. regions, and that individually, each of the BEA areas experience the Carter-Reagan buildup. The Far West region, which contains California, is clearly the leader in attracting contract dollars. In contrast, the Rocky Mountain region receives the lowest level of real MPCs. Because of these large differences in MPC values in different states, there may be important differences in the economic responses to a MPC shock. This topic will therefore be analyzed further in Section III.F.

Labor productivity data have been computed by taking the natural logarithm of real GDPS per state worker. GDPS is from the BEA and the state employment numbers are total non-farm employment from the Bureau of Labor Statistics Current Employment Statistics survey. The aggregate GDP deflator was used to convert nominal variables into

[4] New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains, and Far West.

real terms. Population estimates, used to scale the MPC data in Figure III-1, are also downloaded from the BEA webpage.

The state-level patent data are from the NBER patent database. Hall, Jaffe, and Trajtenberg (2001) contain a description of this data set. These data contain all utility patents granted between 1963 and 1999. This chapter chooses to sort the patent data by application year in order to use the date most closely associated with the date of invention. Using the application date is superior to using the date of grant since budgetary resources fluctuate across time at the USPTO, which leads to budgetary variations in the application-grant lag. However, the application year is only reported for patents granted since 1967. This thereby limits the time dimension of the analysis.

Patents that have been applied for before 1999 but which have not been granted until after 1999 are not included in the NBER patent database. This can lead to potential truncation problems in the data. According to Hall, Jaffe, and Trajtenberg (2001), in most sub-periods, 95% of the patents in the database have been granted within 3 years of the application. To account for potential truncation problems, the sample period for this analysis is therefore limited to end in 1995. As such, this chapter chooses to focus on the sample period 1967-1995 which includes the Carter-Reagan military buildup.

Figures III-3 and III-4 plot the patent data. The former shows the cross-state variation in utility patents granted as a share of each state’s population. This quintile map indicates that areas such as California and Illinois have a high rate of patenting even though they have large populations. Other areas such as Alabama and Maine have lower than average patenting during the Carter-Reagan buildup. Figure III-4 shows the time series variation in patenting across the eight BEA regions. These data show that there are substantial differences in the number of patents across regions. However, each region clearly follows an aggregate trend. In the analysis that follows this time series trend will be explicitly accounted for by demeaning the data.

In the analysis, EMP is used to abbreviate non-farm employment by state, LP denotes labor productivity and PAT stands for utility patents granted and sorted by application year.

The following analysis examines the economic effects of an increase in MPC awards at the state level. This is preferred to analyzing military base closures, which may not be exogenous to the economic conditions at the state level. On the contrary, several papers have argued that the allocation of MPC awards at the state level of spatial aggregation is uncorrelated with regional economic activity. Mayer (1991), Blanchard and Katz (1992), and Hooker and Knetter (1997) argue that state procurement spending is not distributed based on the local economic conditions. Mayer (1991) concludes on the politics of distribution of defense contracts by the Congress that “There is little systematic evidence that members vote against their policy preferences on weapon programs because of local economic impact; the Pentagon does not, indeed cannot, distribute defense contracts (as opposed to bases) for political purposes.”[5] Furthermore, Hooker and Knetter (1997) perform Granger causality tests and find evidence supporting the exogeneity hypothesis.

[5] Mayer (1991) page 210.

III.D. Methodology

The estimated system is a balanced panel vector autoregression (PVAR) with p lags and m variables. The system of equations can be written as follows.

$$w_{nt} = c + \sum_{l=1}^{p} \Phi_l \cdot w_{nt-l} + e_{nt}$$

$$e_{nt} = \lambda_t + \alpha_n + \varepsilon_{nt}, \qquad \text{where} \quad \varepsilon \sim N(0,\Omega)$$

and $$E\left(\varepsilon_{nt}\varepsilon_{rs}^{'}\right) = \begin{cases} \Omega & for \;\; n = r,\, t = s \\ 0 & otherwise \end{cases}$$ for $t = 1,\ldots, T$ and $n = 1,\ldots, N$.

w_{nt} is an $m \times 1$ vector of variables for state n at time t. Φ_l is an $m \times m$ matrix of coefficients and c is a constant term. λ_t is a constant term that is common across states but varies across time. This variable takes into account that all states may be influenced by aggregate macroeconomic factors that vary over the business cycle. α_n is a state-specific effect, which is constant across time but varies across regions. This allows for individual effects that influence the states differentially. Lastly, ε_{nt} is a vector of errors. The variance-covariance matrix Ω is common for all states across time, corresponding to the assumption of homogeneity across regions. Both α_n and ε_{nt} have zero means and are independent among themselves and with each other.

To estimate the system, we remove the aggregate time effect and the constant term by subtracting the mean across states from all observations. This yields the following equation:

$$w_{nt} - w_{\bullet t} = \sum_{l=1}^{p} \Phi_l \cdot \left(w_{nt-l} - w_{\bullet t-l}\right) + \alpha_n - \alpha_\bullet + \varepsilon_{nt} - \varepsilon_{\bullet t}\ .$$

Let $y_{nt} = w_{nt} - w_{\bullet t}$, $c_n = \alpha_n - \alpha_\bullet$, and $u_{nt} = \varepsilon_{nt} - \varepsilon_{\bullet t}$, then the equation can be written as

$$y_{nt} = \sum_{l=1}^{p} \Phi_l \cdot y_{nt-l} + c_n + u_{nt}.$$

The chapter estimates this system by OLS. In general, under the assumption of a fixed T and $N \to \infty$, the OLS estimator is inconsistent. Under this assumption, the first difference of the system can be estimated by GMM with Anderson-Hsiao (or Arellano and Bond) instruments. However, if we assume big T then the model can be consistently estimated by OLS. With a sample length of 29 time periods, T is assumed sufficiently large to not cause problems with OLS inconsistency or with narrow standard error bands as discussed in Cao and Sun (2006). As such, the system of equations is estimated with 50 states and the District of Columbia and observations from 1967 to 1995, adding up to a total of 1479 observations.

In order to estimate a panel vector autoregression, the appropriate lag length must be chosen. Some contracts last two or three years and including only one lag in the regressions may therefore introduce omitted variable bias. Therefore, the benchmark estimations include three lags. However, the impulse response functions are generally robust to changing the lag length, and many results are shown also when including only two lags.

To estimate the impulse response functions, an orthogonal shock must be identified. This is obtained through a short-run Cholesky decomposition. The recursive ordering with the MPC variable placed last in the ordering allows changes in MPCs of each region to be affected by contemporaneous changes in economic and technological indicators such as GDPS, EMP, or the technological advances made in the given area. Standard errors are estimated by Monte Carlo with 2000 simulations.

III.E. Empirical Results

This chapter of the dissertation now presents impulse response functions from bivariate PVARs. The horizontal axis of each response function corresponds to the forecast horizon in years, with year 1 denoting the time of the shock. The responses are depicted together with 90 percent confidence intervals.

III.E.1 Bivariate Panel Vector Autoregressions

Figure III-5 shows that a MPC shock leads to a significant and long lasting increase in real GDPS a few years after the shock. This corresponds to the findings of Blanchard and Perotti (2002) and Ramey and Shapiro (1998) who at the aggregate macroeconomic level find that output is positively affected by a shock to government defense spending. From Figure III-5, it can also be seen that an increase in RGDPS only has a small positive effect on MPC awards after several years. This indicates that MPCs are not primarily awarded to states with good economic conditions. Specifically, there is no evidence of MPCs being awarded to regions with low economic output in order to stimulate that particular region. This result thereby confirms existing findings in the literature that MPCs are not allocated based on state economic activity.

The response of EMP to a MPC shock is depicted in Figure III-6. As was the case with real GDPS, MPCs lead to a significant increase in employment after four years. This increase in employment is consistent with results found by Hooker and Knetter (1997) and Davis, Loungani, and Mahidhara (1997). However, the positive effects on both real GDPS and EMP are similar in sign and magnitude. As a result, productivity mainly responds insignificantly positive to an MPC shock. This is depicted in Figure III-7, where

Panel A shows the results with two lags and Panel B displays the three lag response functions.[6] Though Figure III-6 indicates that MPCs may increase in the long run after an increase in EMP, Figure III-7 shows that defense spending is not awarded based on state-level productivity shocks.

In order to examine if MPCs lead to the development of new technology, this chapter estimates the system with patent application data as a measure of technological progress. When comparing Figure III-1 with Figure III-3 it can be seen that there is no clear connection between states with active patenting and those that are awarded large MPCs. There are states, such as Mississippi, that do very little patenting while being awarded many MPCs. Others, such as California, are awarded a substantial number of contracts and do a great deal of patenting. The correlation between the data used in the two figures is 0.19, indicating a positive but small relationship between the time series averages. Since the cross-state variation of prime contracts across the U.S. is relatively high, it is of interest to examine states with many or few military contracts separately. Therefore, Section III.F. below examines the empirical results when only certain subgroups are considered. First, however, the average aggregate results are examined.

To estimate the effect on the development of new technology of a military expenditure shock, PAT is ordered first in the system, as it is expected to take time to develop a new technology. This also allows MPCs to be awarded to areas with technologically advanced production. Panels A and B of Figure III-8 depict the results from estimating the PVAR with two and three lags, respectively. Indeed, the chapter

[6] Excluding Alaska, Hawaii, and the District of Columbia for the analysis improves the significance of the LP results and does not change the overall shape of the response functions.

finds that military spending leads to a significant increase in the arrival of new inventions, corresponding to the results found in Chapter II at the firm level. Furthermore, there is only weak evidence of contract awards being allocated to areas that have developed a new technology. Specifically, a patent shock only leads to small positive effects on MPC awards at the long horizon and this response is insignificant if estimated with two lags.

In the mid-1980s, the U.S. experienced a surge in the annual number of patent applications. This surge, which can be seen in Figure III-4, could potentially be associated with changes in the U.S. patent laws. Specifically, in 1980 the Bayh-Dole Act allowed universities and small businesses to retain title to patents on inventions that were made because of federally funded research. This was made possible as long as the patent holder granted a non-exclusive, non-transferable license to the federal government to practice the invention. Furthermore, in 1983 this patent policy change was extended to include large businesses. The surge in patenting in the mid-1980s could therefore be a result of the change in patent law and of an increase in the incentives to invent and innovate. However, Kortum and Lerner (1998) examined this issue. They found that the surge in patenting could be interpreted as a surge in overall U.S. scientific development. The working hypothesis in this chapter is therefore that the surge in patenting is not a result of patent law changes.

To account for possible confounding effects of patent policy changes, this chapter also estimated the patent impulse responses separately for the pre- and post-1984 periods. These response functions are depicted in Panels A and B of Figure III-9. Two lags are included because of the shorter sample length. The impulse responses show that the patent law change is not the cause for the increase in patenting after a MPC shock. Both in the pre- and post-1984 periods, patents respond significantly positively to an MPC shock, and the positive response is longer lasting in the early part of the sample compared to the post-1984 results. In addition, Figure III-9 confirms that MPCs are not awarded to states based on the development of new technology as the lower left graphs of Panels A and B do not show significant responses of MPC awards to a patent shock.

III.E.2 Trivariate Panel Vector Autoregressions

To take into account possible omitted variable bias, the impulse response functions were also computed when including three variables in the PVAR. Figure III-10 displays the responses to an MPC shock in a PVAR with PAT, real GDPS, and MPC. When controlling for real GDP, the positive response of PAT to an MPC shock remains significant. In addition, the response of real GDPS to an MPC shock is significantly positive with long-lasting effects.

Panels A and B of Figure III-11 report the results from a PVAR with PAT, EMP, and MPC. Panel A reports the results using two lags and Panel B shows the response functions using three lags. As was the case in the bivariate systems, an MPC shock leads to an increase in both PAT and EMP. However, the significance of the PAT response is now somewhat sensitive to the number of lags included in the PVAR. In the case of three lags, PAT responds significantly positively immediately after the shock. However, when two lags are included, the response tends to increase, but is insignificant at the short-run forecast horizon.

The corresponding results from a PVAR with PAT, LP, and MPC are shown in Panels A and B of Figure III-12. PAT continues to respond positively and the result is robust to changing the lag length. Additionally, as was the case with the bivariate systems, the response of LP is insignificantly positive. When three lags are included, the lower left response function of Figure III-12 Panel B indicates some evidence that MPC awards at the long horizon may be channeled to areas with new, effective technology. However, the response is only significant at the long horizon and is not present when the PVAR is estimated with two lags.

III.F. Subgroups of States

As seen from Figure III-1, the 51 regions receive very different amounts in MPCs per person. Table III-2 organizes the states into quintiles based on the average real prime contracts controlling for state population. This grouping method follows Hooker and Knetter (1994). It can be seen that the large prime contracting states, such as California and Missouri, still remain in the top quintile when their MPC values are normalized by population.[7]

Table III-3 provides the average annual real MPC dollar values and standard deviations within each quintile. That table illustrates that the average annual contract amount per person varies considerably between quintiles. Indeed, quintile 5 receives contract amounts that are an order of magnitude larger than the corresponding contract awards in quintile 1. Additionally, the variation around the average amount of MPCs per person is relatively large, indicating that the panel vector autoregressions should continue

[7] The analysis was also preformed excluding Alaska, Hawaii, and the District of Columbia, and the results were robust to this change.

to include an individual coefficient as there may be some within group variation that cannot be accounted for with a single intercept for all states.

Figure III-13 through Figure III-16 displays the responses of real GDPS, EMP, LP, and PAT to an MPC shock in bivariate PVARs for each quintile. With the smaller sample size, some responses now become insignificant. However, important information can still be drawn from this analysis. Figure III-13 shows how the 20 states in quintiles 1 and 2 are positively affected by an MPC shock, while the remaining groups are not significantly affected at any horizon. Furthermore, the states in quintiles 1 and 2 tend to depict very long-lasting effects. This figure therefore shows that the aggregate effects of an increase in military spending, which were found in Figure III-5, mainly occurred because of economic consequences for the small military states.

Figure III-14 plots how EMP is not significantly affected at any horizon for any of the subgroups. This indicates that any effects on labor productivity are mainly a result of adjustments in output and not through changes in the number of workers employed. However, the response of EMP in quintile 2 does become significant in the long run if one, four, or five lags are included in the PVAR (not shown). This supports the finding that the economic conditions in states with relatively small amounts of spending per state capita may be positively affected by a military shock to a greater extent than large military states. However, these results run counter to the findings of Hooker and Knetter (1994) who find that small military states experience an insignificant decline in unemployment rates after a decrease in military spending.

Although output and employment only experience small adjustments, labor productivity defined as output per employed worker may be significantly affected. Figure

III-15 shows this to be the case. Labor productivity in quintile 1 increases significantly shortly after the MPC shock, and quintile 2 increases over time. Surprisingly, the large military areas tend to experience only small or negative effects on productivity of a MPC award, again clearly indicating how subgroups within the U.S. are affected differently. Figure III-16 reports the results from bivariate PAT analyses for the quintiles. Quintiles 1 and 2 are again positively affected, indicating that new technology is being developed because of the prime contracts. Interestingly, the states that experience increased labor productivity after an increase in MPCs are also states that develop more new technology. For the large prime contracting states the PAT response functions are generally insignificant.

The results in this section point toward important differences in economic responses to increased military spending across the United States. Specifically, it is of interest that states that develop a significantly increased amount of new technology, evidenced through a significant increase in patenting, also experience a positive effect on labor productivity. Together with the result that employment is only insignificantly affected, and that the main adjustment therefore happens through positive effects on the production of goods, these response functions indicate that the new technology indeed has been introduced in the affected states. However, more evidence is needed on this area of research.

The results found in this chapter of the dissertation help to understand how aggregate U.S. economic effects occur because of underlying regional fluctuations. Existing studies that have focused on the U.S. as an aggregate have reported different economic effects of defense spending. Chapter III has found that not only is output positively affected by military spending, but the average state has also been shown to develop more new technology because of defense contracting. This may partly be a result of the research and development contracts that are inherent in the aggregate MPC numbers. Furthermore, these findings correspond to the results found in Chapter II of this dissertation. That chapter showed that large military prime contractors increase company-contribution to research and development after a MPC award, indicating that new technology is being developed.

III.G. Conclusion

This chapter examined the consequences for regional productivity and technological progress of an increase in military spending. The data for this study covered the Carter-Reagan military buildup, which provided variation in the data series. Furthermore, the dollar amount of MPC awards varies considerably across states, as does the annual amount of patenting.

Using U.S. data on MPC awards, GDPS, employment, and patenting from 1967 to 1995 for the 50 states and the District of Columbia, the chapter estimated a panel vector autoregression. From an analysis with all 50 states and the district, the study found that output and employment increase following a MPC shock. However, these positive responses are close in magnitude, leading to insignificant effects on state labor productivity. The number of patents increases strongly after increased military spending, providing evidence that new technology is being developed as a result of the increased expenditure.

Next, this chapter divided the states and the district into quintiles in order to examine how states with different amounts of prime contracts responded to a military spending shock. Interestingly, the analysis found that states with relatively few contract dollars per person responded more positively to an expenditure shock than did relatively large military states. These results add to the existing literature by showing that U.S. macroeconomic effects arise based on state responses that differ across the country.

Acknowledgement: I thank Lone E. Christiansen for co-authoring Chapter III. As the dissertation author, I am a primary investigator and author of this chapter. I have permission from Lone E. Christiansen to use this chapter within this dissertation. A previous version of Defense Spending, Productivity, and Technological Change: A Regional Approach (Chapter III) appears in Lone E. Christiansen's 2007 UCSD Dissertation, titled "Essays on Productivity, Technology, and Economic Fluctuations".

III.H. Tables and Figures

Table III-1: Average Annual Dollar Value of Real MPC by State

State Name	MPC	State Name	MPC
Alabama	1,578	Montana	130
Alaska	507	Nebraska	271
Arizona	2,157	Nevada	163
Arkansas	473	New Hampshire	556
California	27,381	New Jersey	3,869
Colorado	1,809	New Mexico	580
Connecticut	6,172	New York	10,331
Delaware	211	North Carolina	1,420
District of Columbia	1,432	North Dakota	211
Florida	4,936	Ohio	4,415
Georgia	2,997	Oklahoma	741
Hawaii	662	Oregon	290
Idaho	64	Pennsylvania	4,307
Illinois	2,030	Rhode Island	455
Indiana	2,671	South Carolina	666
Iowa	638	South Dakota	76
Kansas	1,400	Tennessee	1,362
Kentucky	505	Texas	10,655
Louisiana	1,752	Utah	750
Maine	710	Vermont	214
Maryland	4,031	Virginia	6,393
Massachusetts	7,271	Washington	3,339
Michigan	2,445	West Virginia	211
Minnesota	2,068	Wisconsin	1,105
Mississippi	2,003	Wyoming	93
Missouri	6,487		

Note: MPC denotes the average annual dollar value of military prime contracts from 1967 to 1995 in millions of 2000 dollars.

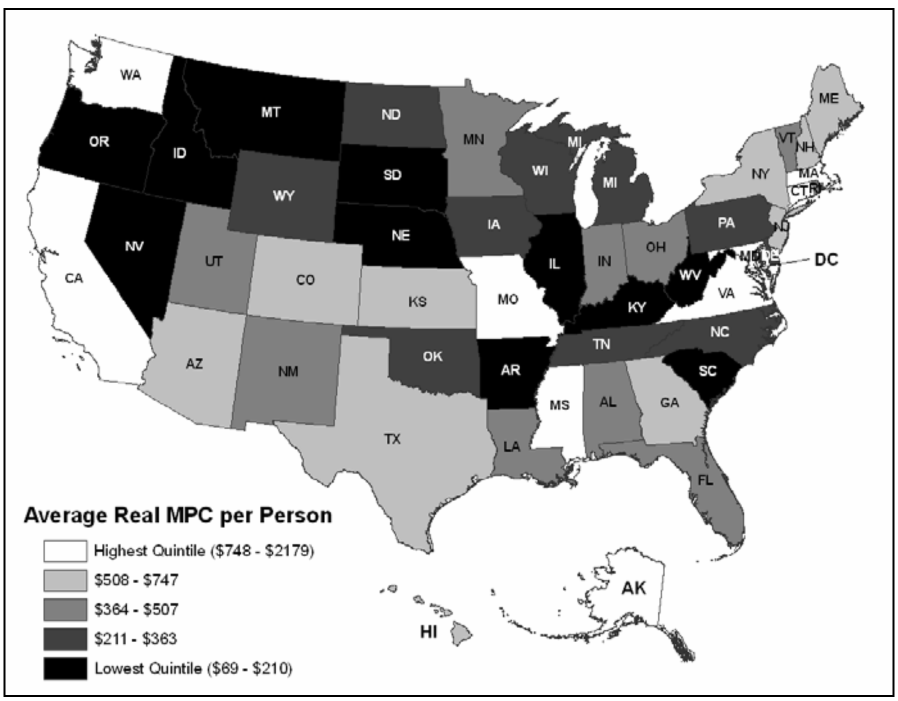
Table III-2: Grouping of States

Quintiles by average real MPC per person			
Quintile 1	Idaho South Dakota West Virginia Oregon Kentucky Montana Nebraska Nevada Illinois South Carolina	Quintile 4	Utah New Jersey Georgia New York Colorado Kansas New Hampshire Maine Hawaii Arizona
Quintile 2	Arkansas Wyoming Iowa Wisconsin North Carolina Oklahoma Michigan Tennessee North Dakota Delaware	Quintile 5	Texas Mississippi Washington Maryland California Virginia Alaska Massachusetts Missouri Connecticut
Quintile 3	Pennsylvania Alabama Ohio Louisiana New Mexico Vermont Rhode Island Florida Indiana Minnesota		

Table III-3: MPC Data by Quintile

	Average MPC per Person	
Quintile	Mean	Standard deviation
1	146	43
2	263	48
3	440	45
4	592	70
5	1,213	466

Note: Quintile 1 contains states with the lowest average dollar value of contracts, and quintile 5 contains states and the District of Columbia which receive the highest average dollar value of contracts. The large standard deviation for average MPC within quintile 5 is a result of the large contract volume in California as seen in table 1.
The left hand columns are normalized by state population, and means and standard deviations are denoted in 2000 dollars.
The right hand columns are not normalized by population, and means and standard deviations are here denoted in millions of 2000 dollars.



Note: The grouping is based on average annual real MPC per person, using data from 1967 to 1995. The lowest quintile has one more region than the other four quintiles.

Figure III-1: Regional Military Prime Contract Awards per Person

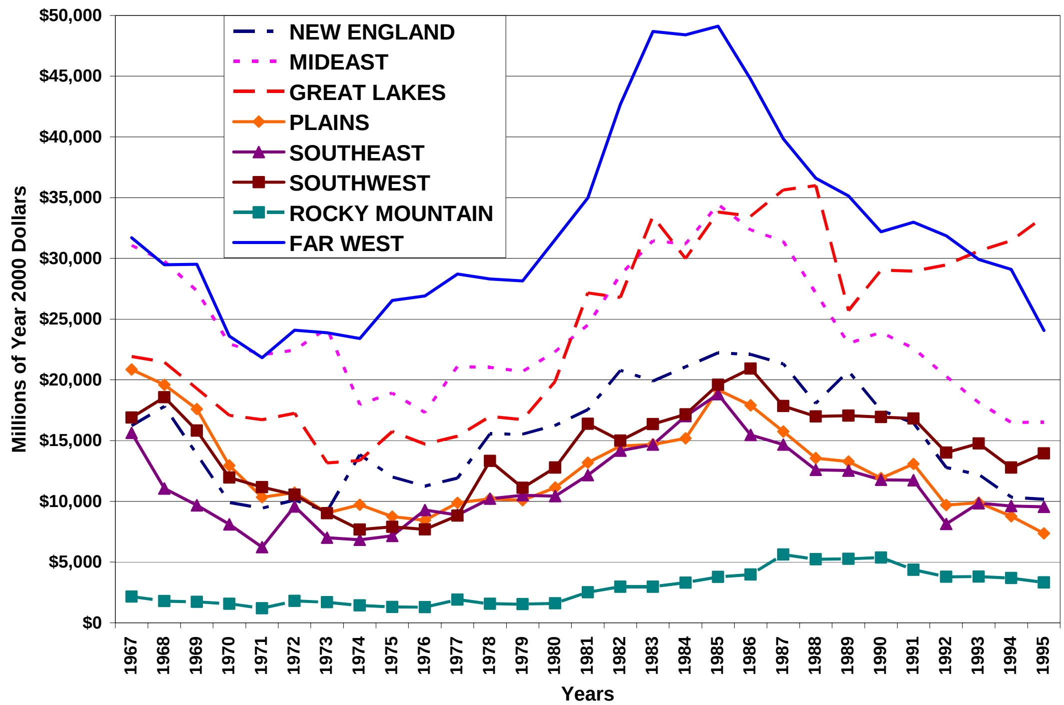
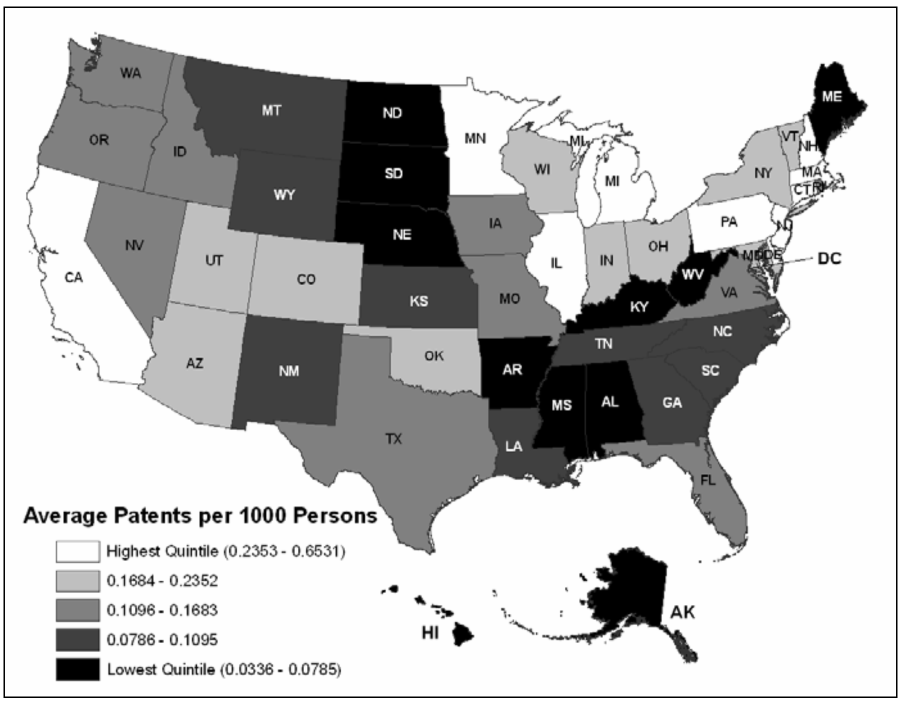


Figure III-2: Real Military Prime Contracts by BEA Region



Note: The grouping is based on average annual number of patents, sorted by application year, per thousand people in the given state or district, using data from 1967 to 1995. The lowest quintile has one more region than the other four quintiles

Figure III-3: Average Utility Patents Granted per One Thousand Persons

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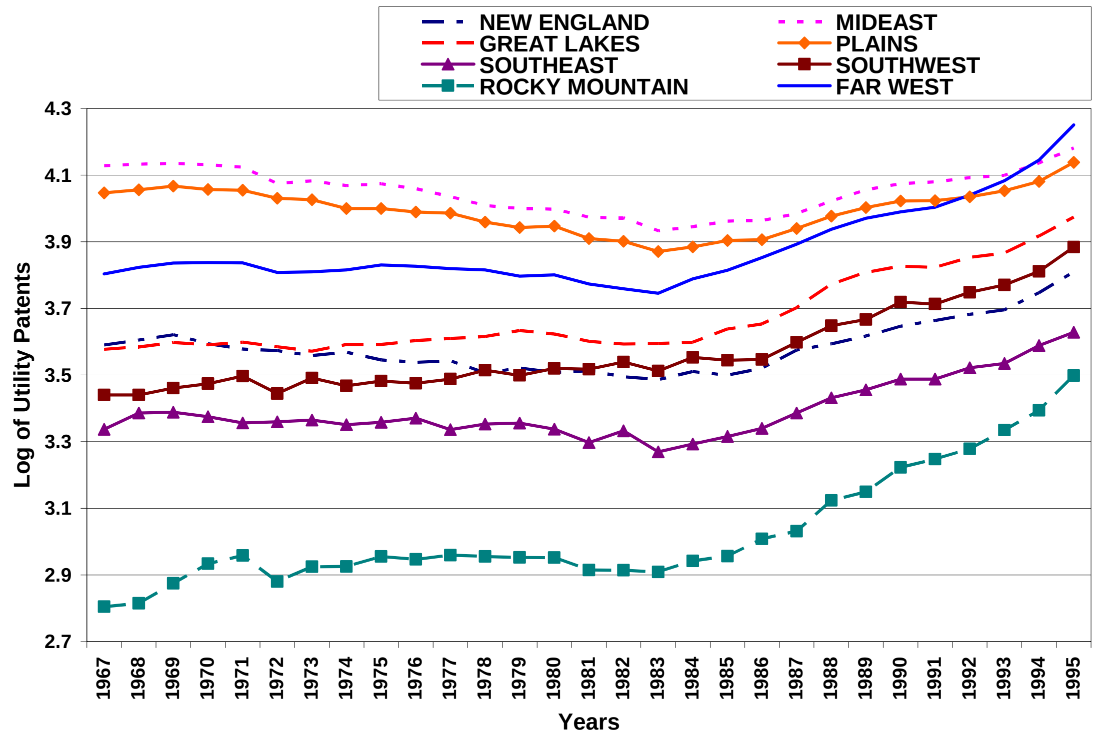
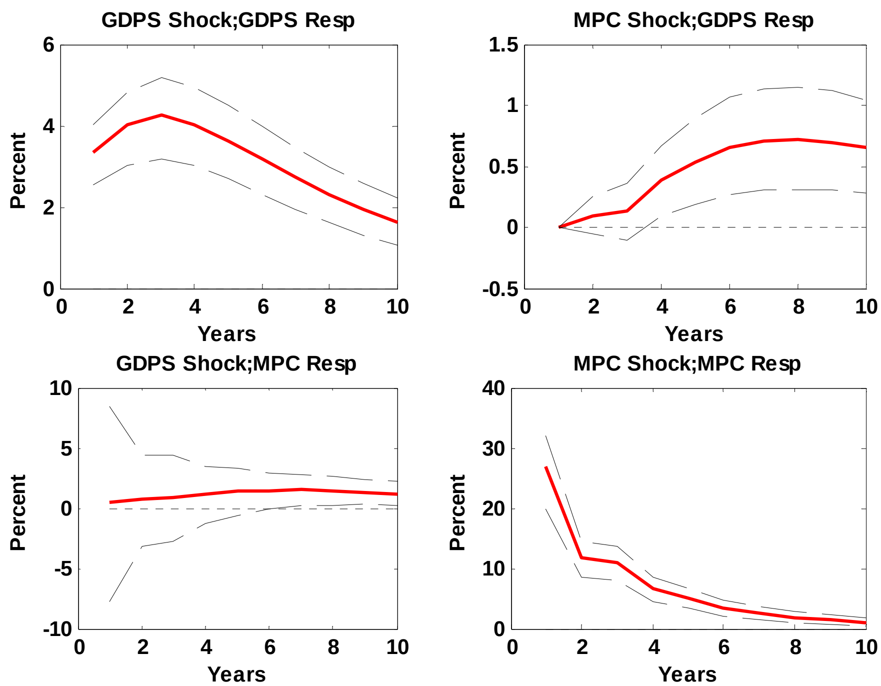
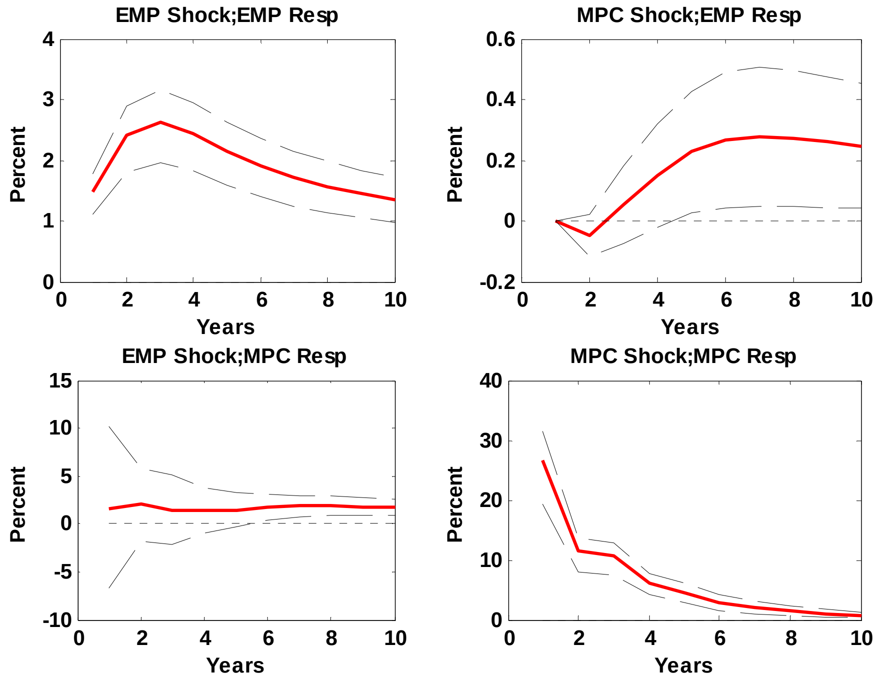


Figure III-4: NBER Utility Patents, sorted by Application Year, organized by the BEA Regions



Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 3 lags are included. Response is abbreviated with Resp.

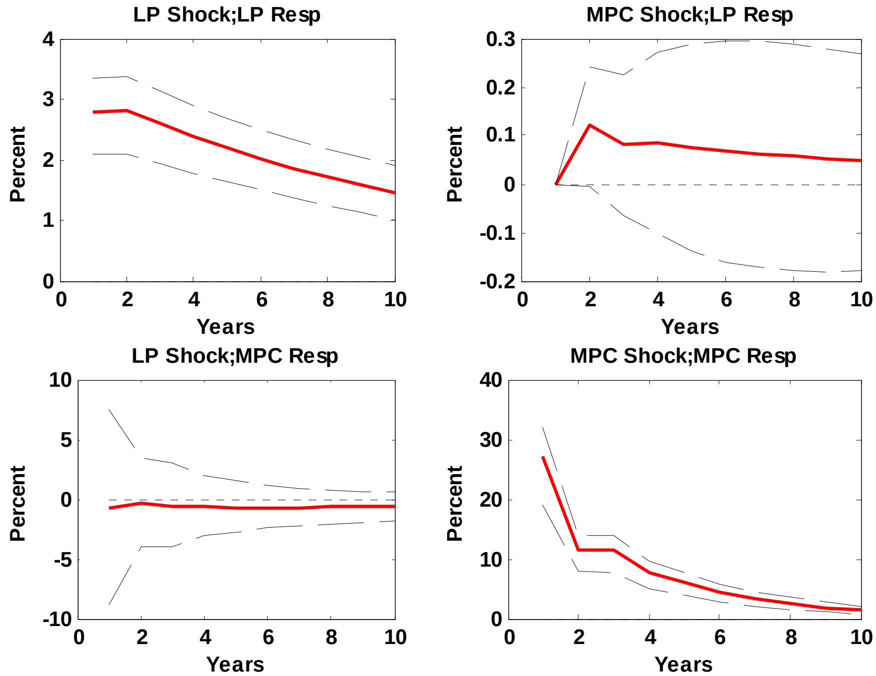
Figure III-5: Bivariate PVAR with Real GDPS and MPC



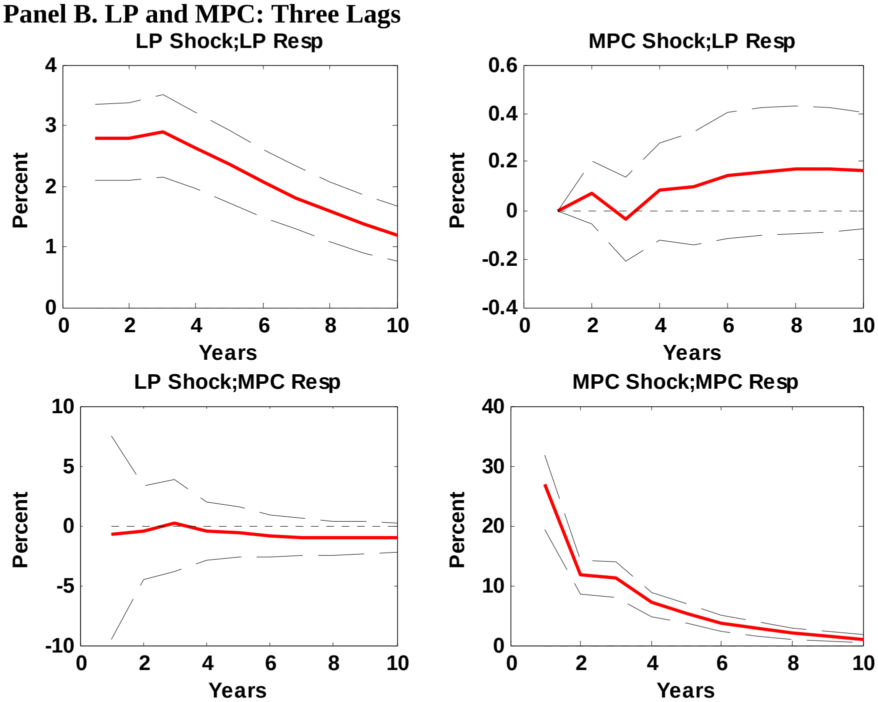
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 3 lags are included. Response is abbreviated with Resp.

Figure III-6: Bivariate PVAR with EMP and MPC

Panel A. LP and MPC: Two Lags



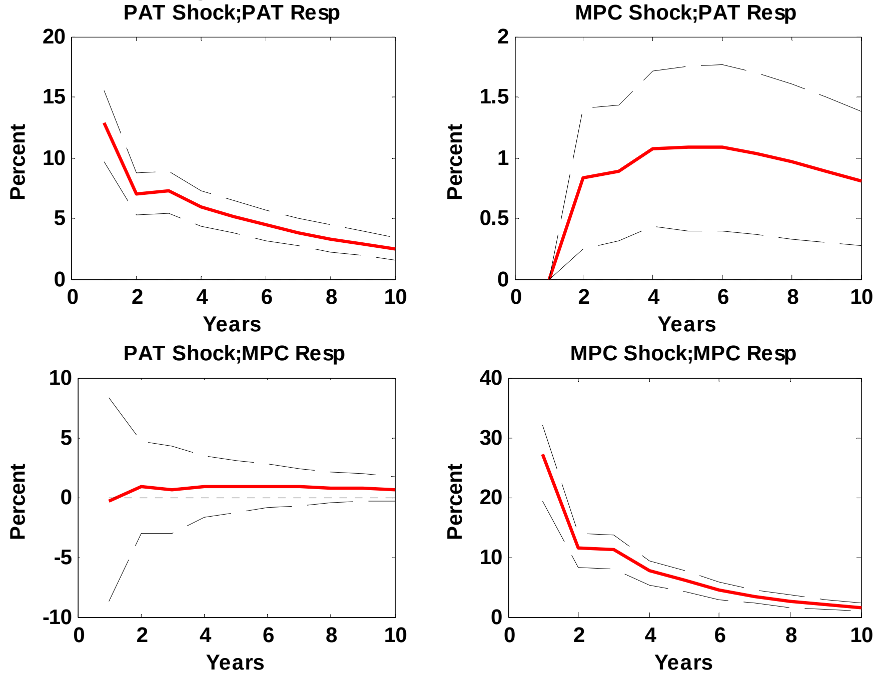
Panel B. LP and MPC: Three Lags



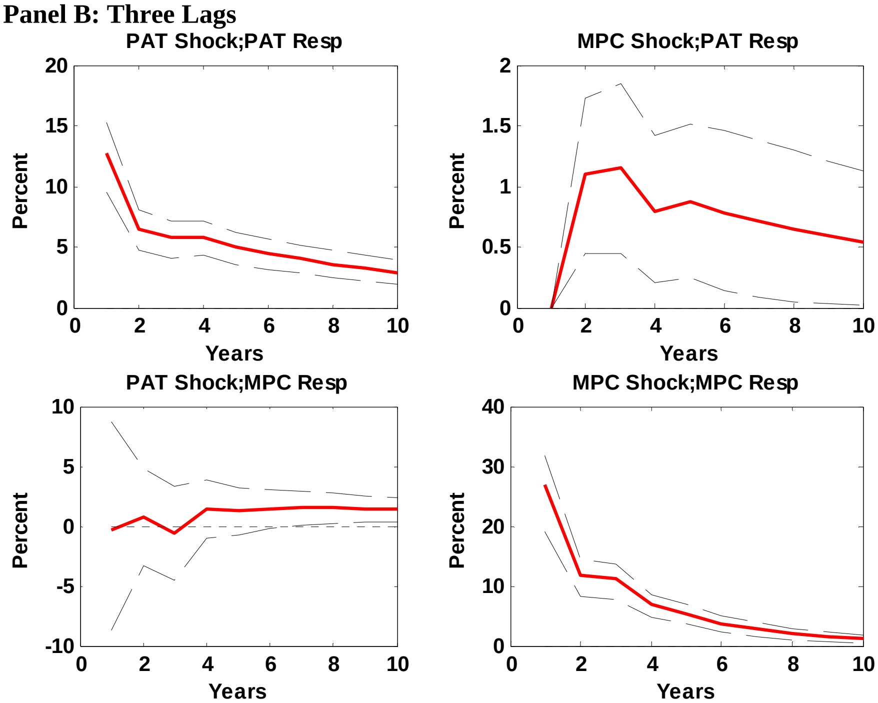
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. Response is abbreviated with Resp.

Figure III-7: Bivariate PVAR with LP and MPC

Panel A: Two Lags



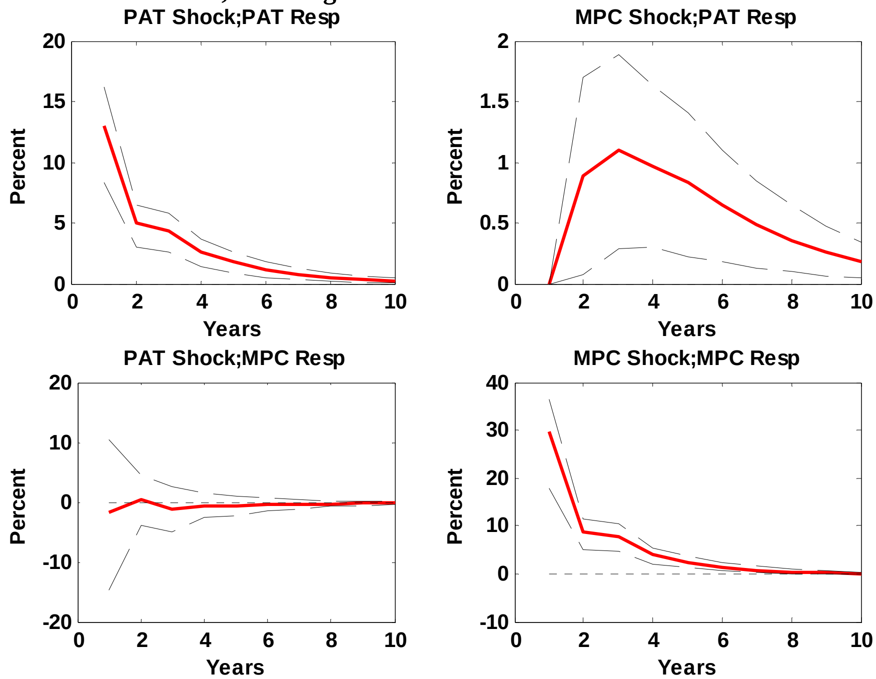
Panel B: Three Lags



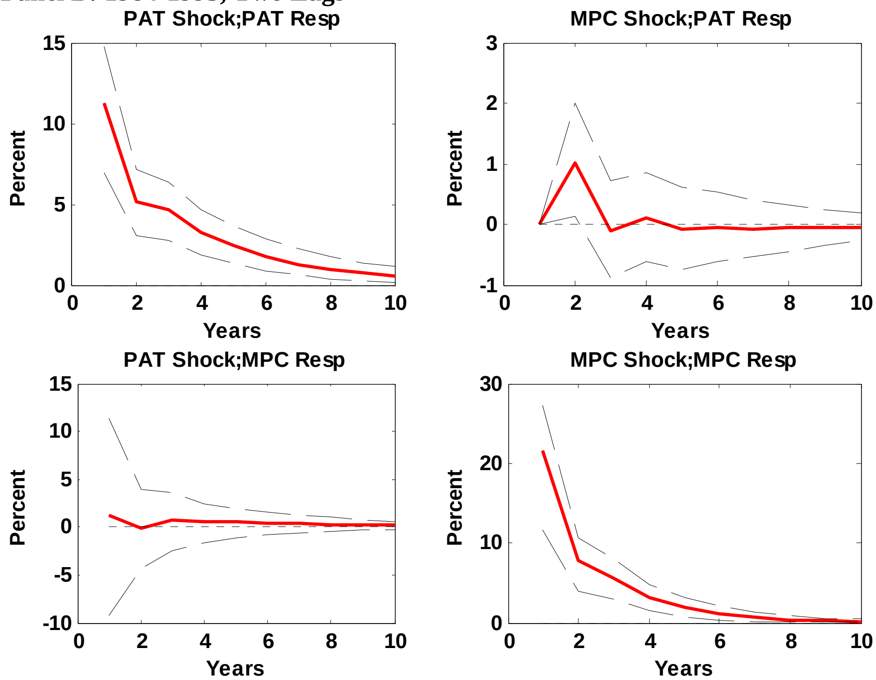
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. Response is abbreviated with Resp.

Figure III-8: Bivariate PVAR with PAT and MPC

Panel A: 1967-1983, Two Lags



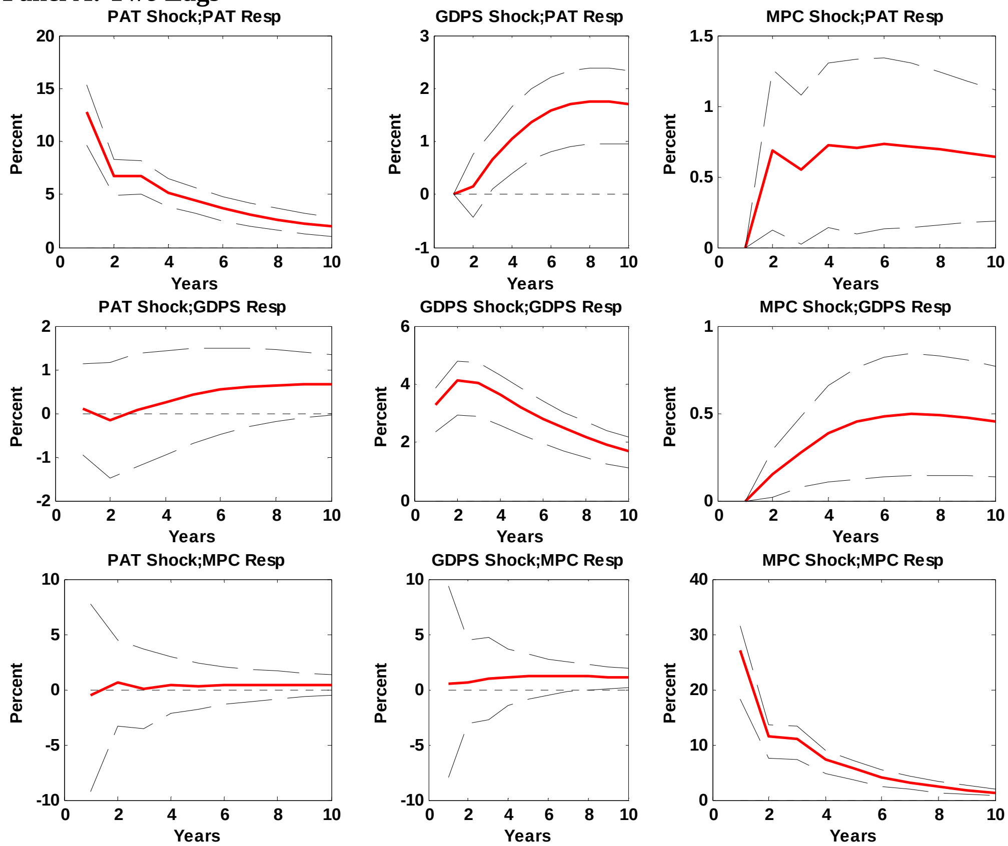
Panel B: 1984-1995, Two Lags



Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. Response is abbreviated with Resp.

Figure III-9: Bivariate PVAR with PAT and MPC, Split Sample

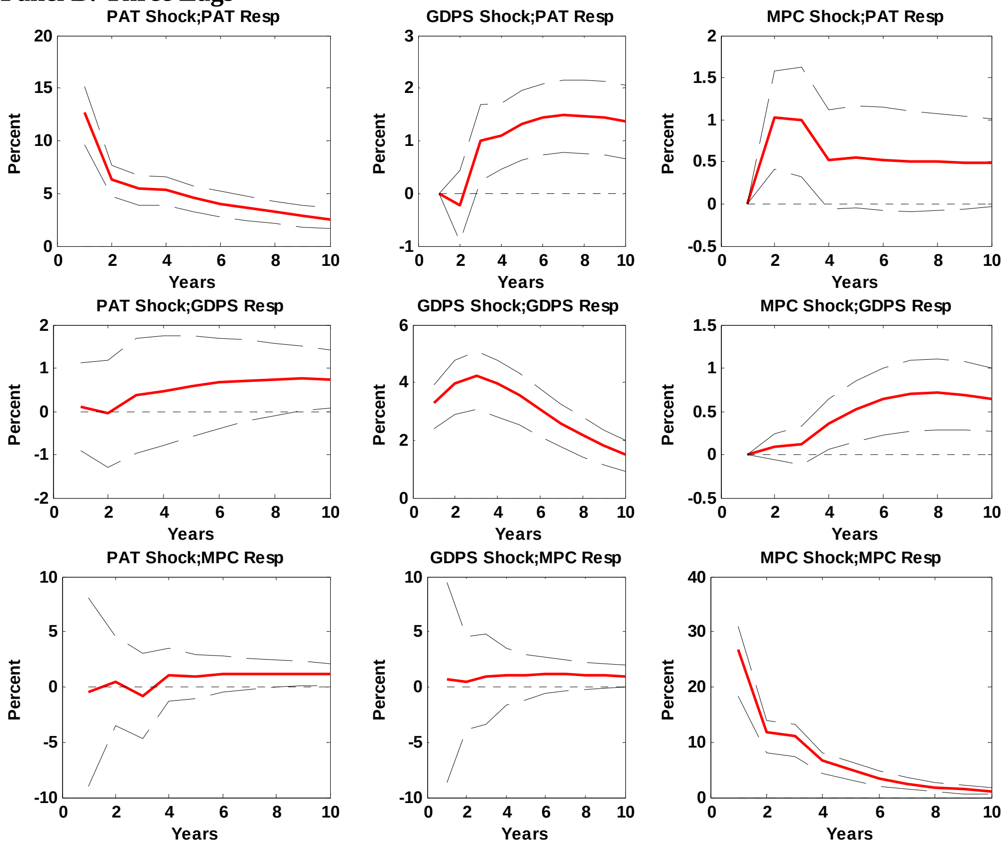
Panel A: Two Lags



Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. Response is abbreviated with Resp.

Figure III-10: Trivariate PVAR with PAT, Real GDPS, and MPC

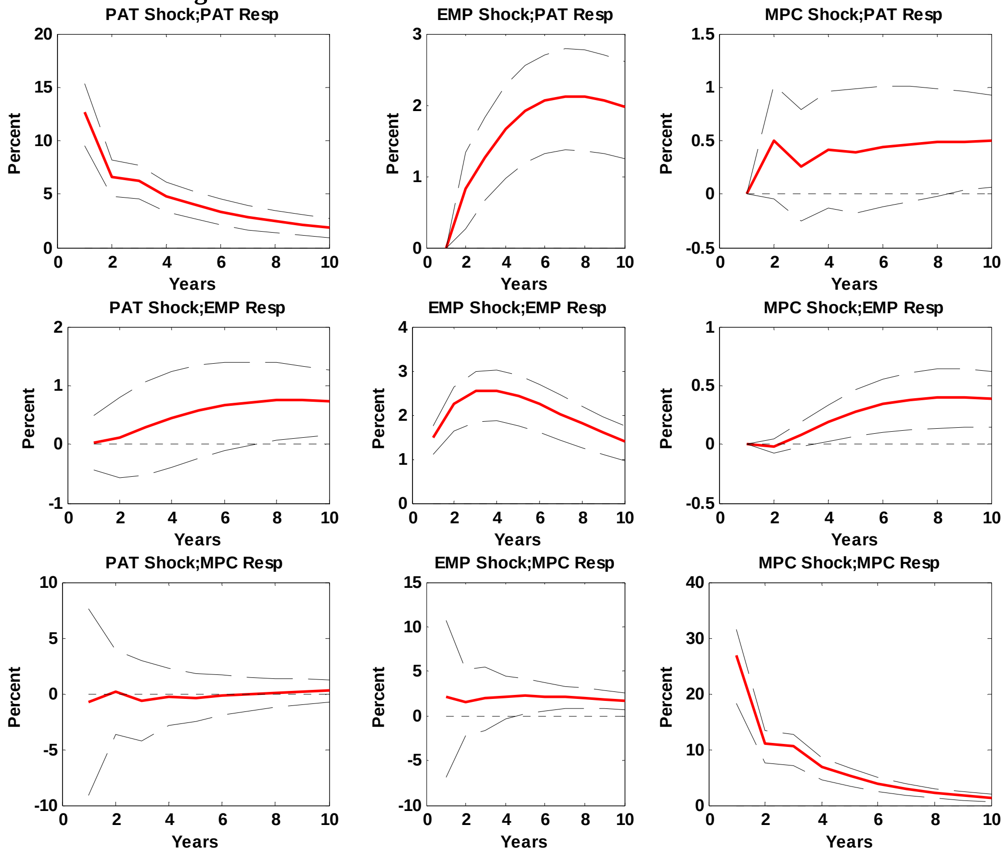
Panel B: Three Lags



Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. Response is abbreviated with Resp.

Figure III-10 (Continued): Trivariate PVAR with PAT, Real GDPS, and MPC

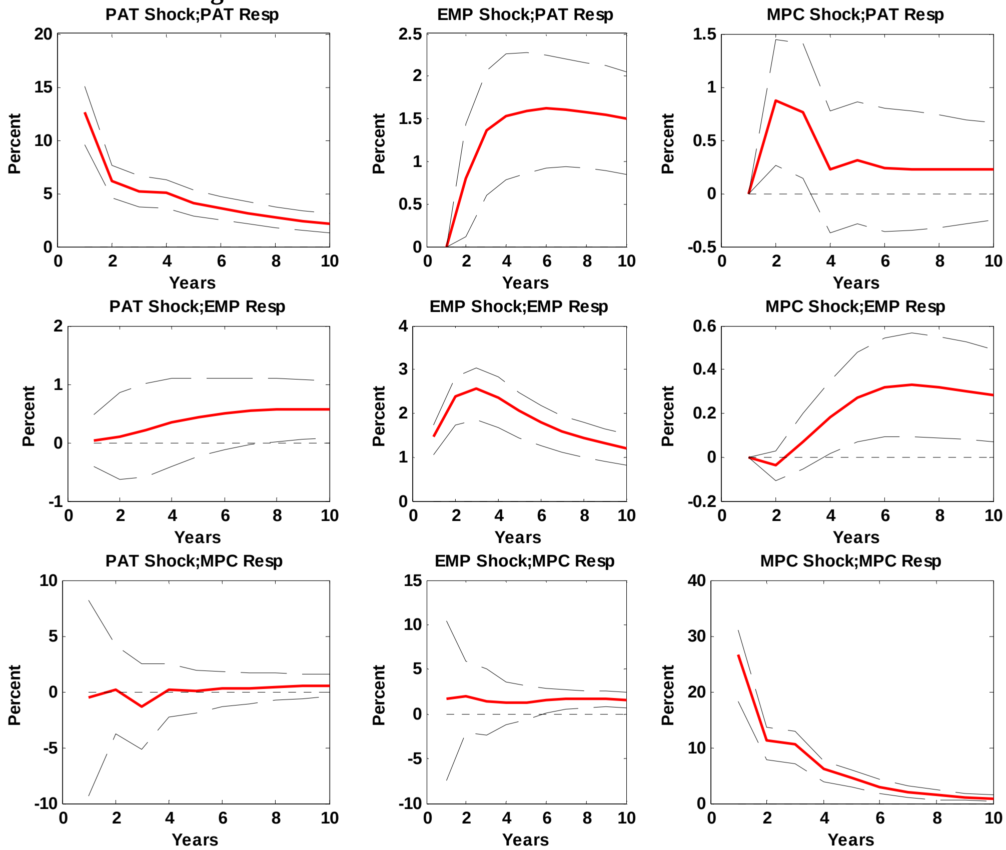
Panel A: Two Lags



Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. Response is abbreviated with Resp

Figure III-11: Trivariate PVAR with PAT, EMP, and MPC

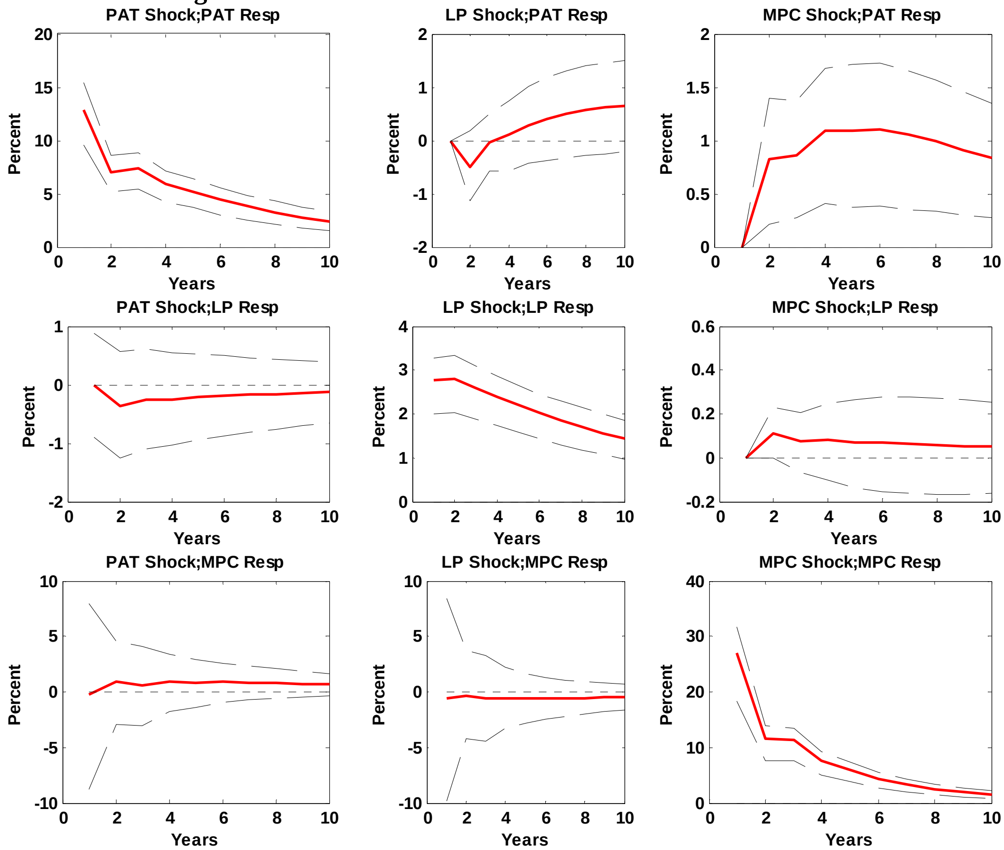
Panel B: Three Lags



Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. Response is abbreviated with Resp.

Figure III-11 (Continued): Trivariate PVAR with PAT, EMP, and MPC

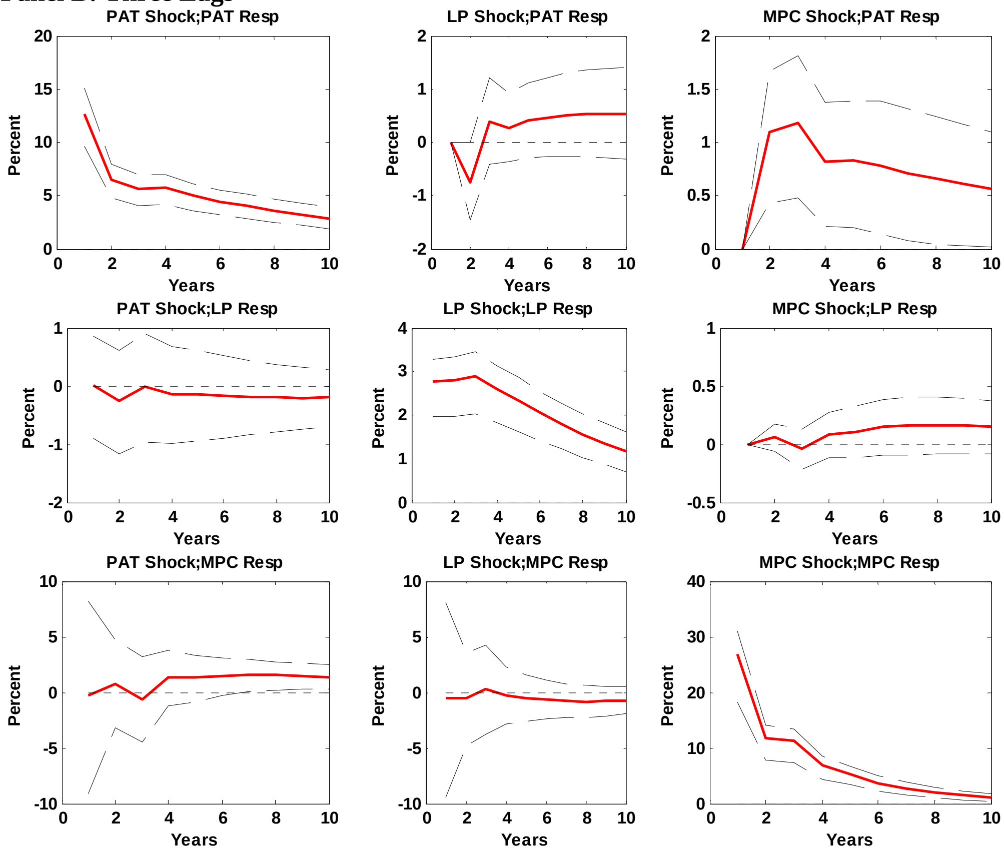
Panel A: Two Lags



Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. Response is abbreviated with Resp.

Figure III-12: Trivariate PVAR with PAT, LP, and MPC

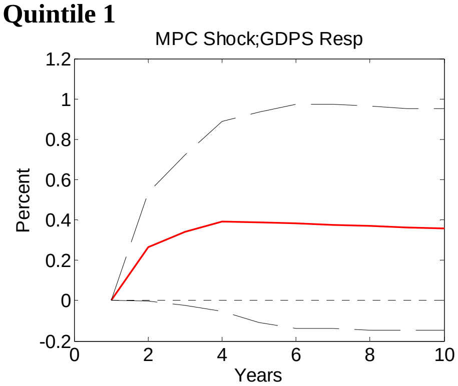
Panel B: Three Lags



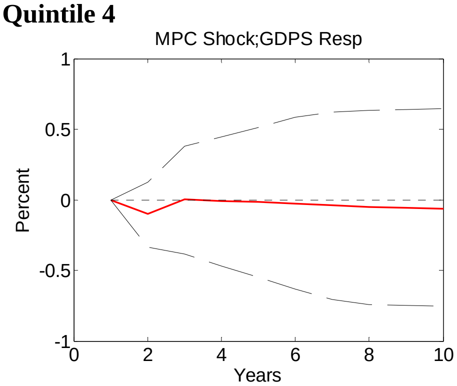
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. Response is abbreviated with Resp.

Figure III-12 (Continued): Trivariate PVAR with PAT, LP, and MPC

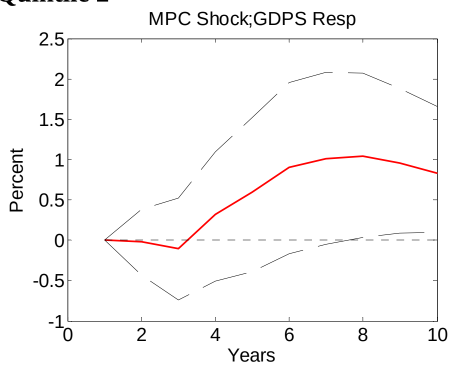
Quintile 1



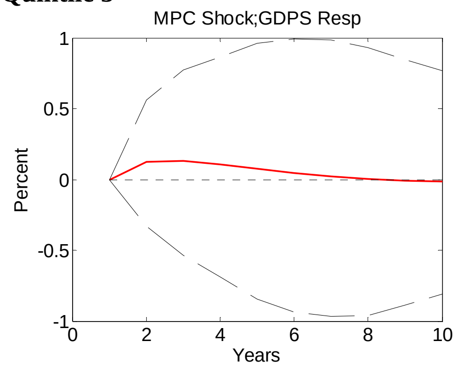
Quintile 4



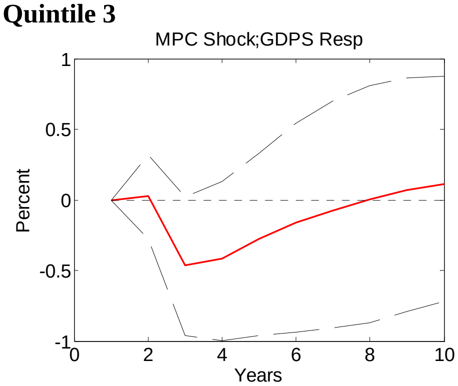
Quintile 2



Quintile 5



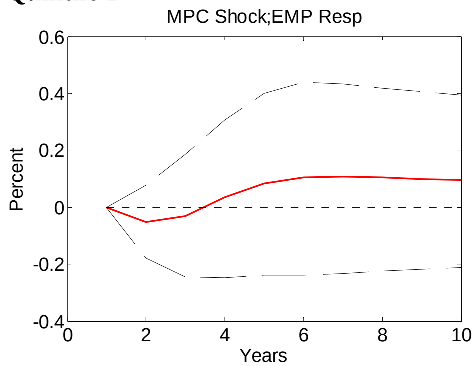
Quintile 3



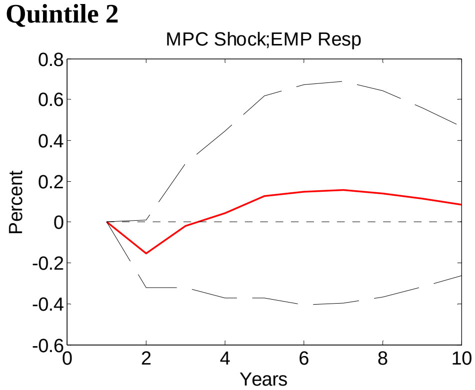
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 3 lags are included. Response is abbreviated with Resp.

Figure III-13: Quintile Bivariate PVARs with Real GDPS and MPC

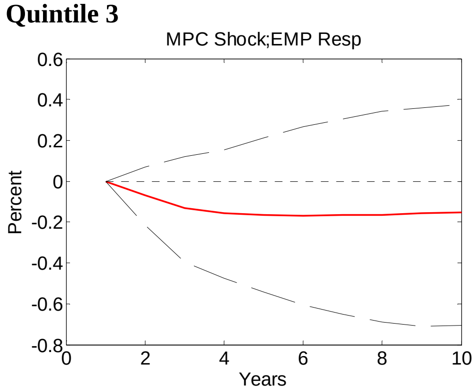
Quintile 1



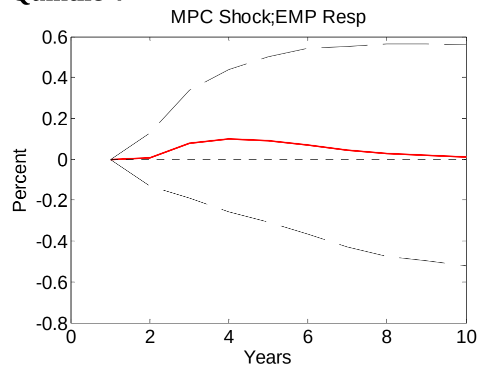
Quintile 2



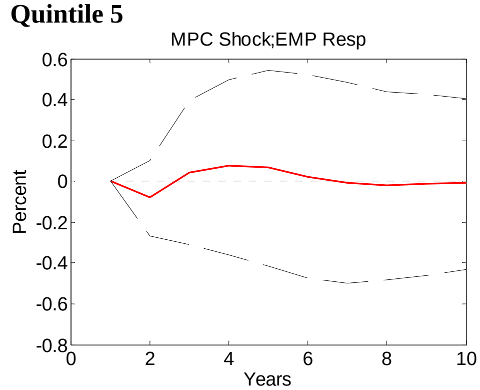
Quintile 3



Quintile 4



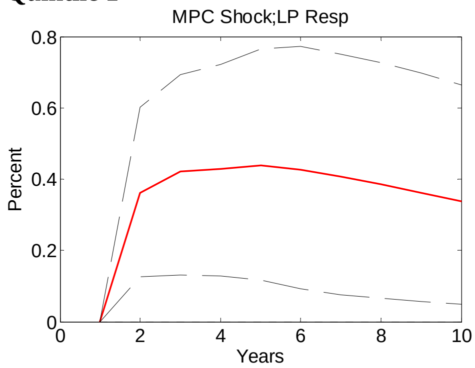
Quintile 5



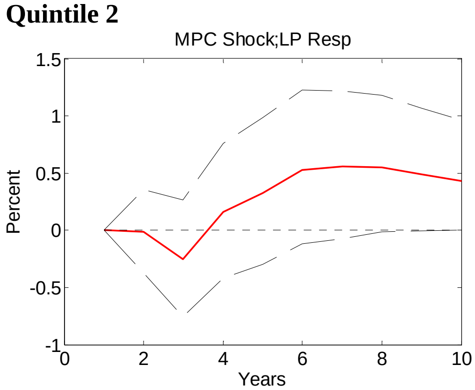
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 3 lags are included. Response is abbreviated with Resp.

Figure III-14: Quintile Bivariate PVARs with EMP and MPC

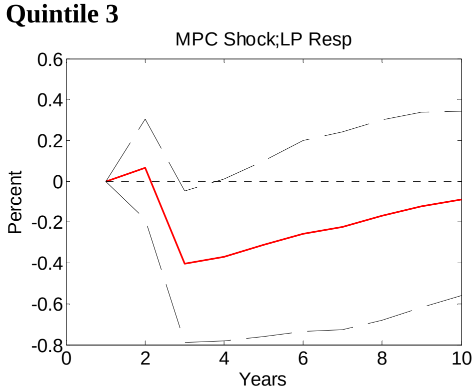
Quintile 1



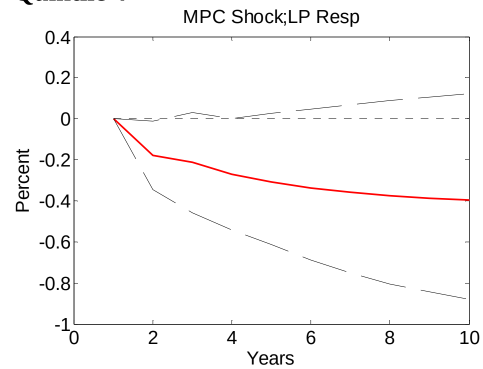
Quintile 2



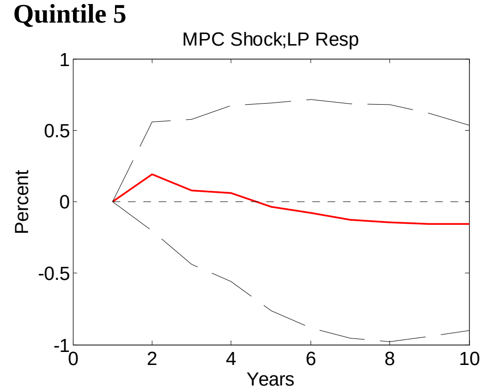
Quintile 3



Quintile 4



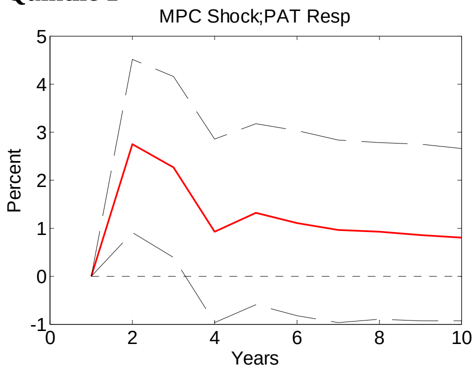
Quintile 5



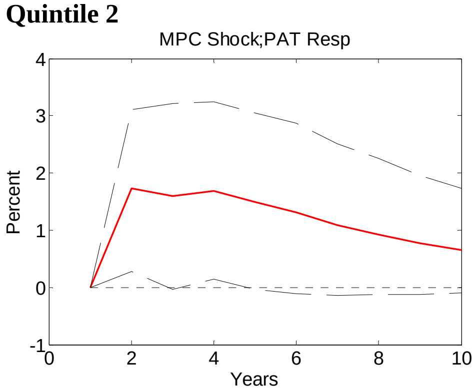
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 3 lags are included. Response is abbreviated with Resp.

Figure III-15: Quintile Bivariate PVARs with LP and MPC

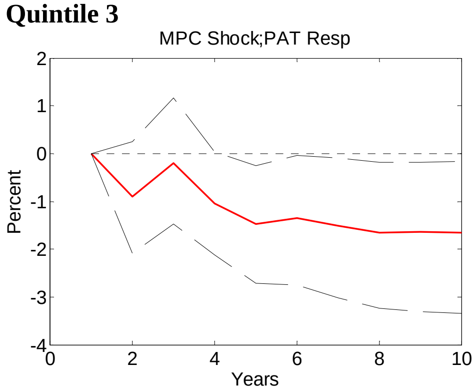
Quintile 1



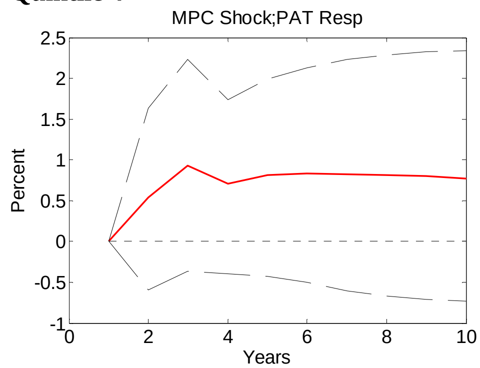
Quintile 2



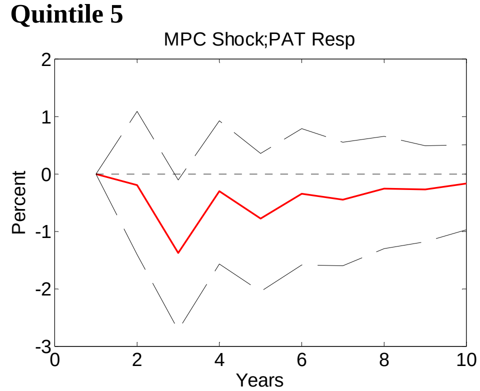
Quintile 3



Quintile 4



Quintile 5



Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 3 lags are included. Response is abbreviated with Resp.

Figure III-16: Quintile Bivariate PVARs with PAT and MPC

III.I. References

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