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Essays on Productivity, Technology, and Economic Fluctuations

A Dissertation submitted in partial satisfaction of the requirements for the degree

Doctor of Philosophy

in

Economics

by

Lone Engbo Christiansen

Committee in charge:

Professor Valerie A. Ramey, Chair
Professor Takeo Hoshi
Professor Nir Jaimovich
Professor Garey Ramey
Professor Christopher M. Woodruff

2007

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2007

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ABSTRACT OF THE DISSERTATION

Essays on Productivity, Technology, and Economic Fluctuations

by

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Doctor of Philosophy in Economics

University of California, San Diego, 2007

Professor Valerie A. Ramey, Chair

Technological progress is one of the main driving forces behind economic growth but how it affects the economy initially is not well understood. This dissertation contains three chapters that examine technological progress and productivity from different angles. They are all motivated by the need for better understanding the economic fluctuations that are observed in the data.

Chapter 1 presents a long time-series of data, dating from 1889 to 2002, in order to examine whether technological progress can lead to temporary slowdowns in productivity growth. In this chapter, patent application data are used as a measure of technological progress. Results show that labor productivity in the pre-WWII period falls below trend temporarily after the arrival of new technology. However, this is not seen in

the post-WWII period when labor productivity slowly starts to increase above trend without initial adverse effects.

Chapter 2, which is co-authored with Bryan Goudie, examines the assumption that technological progress generally is assumed to be exogenous to military spending. The chapter uses firm-level data on military prime contracts together with data on sales per employed worker and patent data in order to explore the effects of military spending on productivity and the development of new technology. The study finds that the number of patents increases significantly as a result of a military prime contract shock, indicating the arrival of new technology.

Chapter 3, co-authored with Bryan Goudie, follows the approach in chapter 2 but examines the effects of military prime contracts at the regional level. The chapter uses U.S. state-level data on military prime contracts, data on gross domestic product by state, and utility patents, sorted by the state of the first inventor. The analysis shows that also 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

Do Technology Shocks lead to Productivity Slowdowns? Evidence from Patent Data

Abstract

This paper provides empirical evidence on the response of labor productivity to the arrival of new inventions. The benchmark measure of technological progress is given by data on patent applications in the U.S. over the period 1889-2002. Through use of vector autoregressions, the analysis shows that labor productivity may temporarily fall below trend after technological progress. However, the effects on productivity differ between the pre- and post-World War II periods. The pre-war period shows evidence of a productivity slowdown as a result of the arrival of new technology, whereas the post-World War II period does not. Positive effects of technology shocks tend to show up sooner in the productivity data in the later period.

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I.A. Introduction

The traditional neoclassical real business cycle model assumes that technology arrives as an exogenous process, after which labor productivity immediately responds positively until the economy eventually converges to the new steady state where labor productivity is permanently higher. However, David (1990), Rogers (1995), and Hall (2004), among others, have provided evidence that technology diffuses slowly throughout the economy. This means that a new technology is adopted by agents over time and that all agents do not adopt the technology immediately. This process of adoption and diffusion of technology takes the form of an S-shaped curve. That is, the technology initially diffuses slowly, followed by a period of rapid diffusion until the speed decreases when the technology has been absorbed in the economy. This view of slow diffusion therefore challenges the notion that technology shocks have immediate and positive effects on the economy. Furthermore, Robert Solow's statement: "You can see the computer age everywhere but in the productivity statistics"¹ clearly states how the literature lacks economic understanding of how productivity is affected by the arrival of new technology.

This paper will show, through use of vector autoregressions and more than a century of data, that labor productivity may respond negatively in the short run to a technology shock. This case can arise if the arrival of a new technology initiates high installation costs or a learning stage for the productive labor. During this stage labor productivity does not necessarily increase as assumed by the standard neoclassical models. Rather, labor productivity can actually fall below trend temporarily. After a time

¹ New York Times, July 12, 1987, page BR36.

lag from when the technology was invented, the technology eventually becomes adopted in the economy and the inflection point of the S-shaped diffusion curve is reached. Inputs can then once again be active in the production process and it is likely that labor productivity will increase above trend.

The existing empirical literature which has focused on technological progress and subsequent productivity slowdown has mainly relied on simple graphical analysis. This paper therefore provides formal statistical evidence that the arrival of new technology can lead to a temporary slowdown in productivity using both an actual measure of technological progress and a long time-series as is important when studying productivity growth. Furthermore, the paper compares differences between the response of labor productivity to technological progress in the Electrification period and the more recent period, when the computer and the internet became widely adopted. The results from the post-World War II (post-WWII) period have important implications for understanding whether technological progress is the main reason for the productivity slowdown observed after 1973.

The focus of this paper is the response of labor productivity and other macroeconomic variables following the initial arrival of new technology. In this paper, technology is measured as new inventions that have experienced a patent application. Because of long diffusion lags, the main focus of this paper is not on long-run impacts on productivity but instead on possible adverse effects in the short run. Therefore, the paper does not argue that there are no positive effects on productivity from new inventions but instead argues that the positive effects may not arrive immediately after the invention of new technology. The contribution of this paper to the macroeconomic literature is

therefore to supply empirical and statistical evidence for how aggregate variables historically have responded to technology shocks in the short run.

As explained in the next section of the paper, much theoretical research has addressed the subject of possible contractionary effects of technology shocks. Further, empirical methods have been employed within the applied microeconomics literature, but this question has not been adequately addressed with long macroeconomic time-series data. The time-series literature therefore lacks direct empirical evidence on the effects of changes in technology.

In this paper, new inventions are measured using historical data on patent applications, extending back to 1889. Using this data set, the paper finds evidence that productivity can temporarily decrease below trend after new inventions arrive. While some macroeconomists argue against the use of patents as a measure of technological progress, it will be argued that problems with patent data are not severe and that the field of macroeconomics can benefit from using patent data, as has long been the case in the microeconomic literature. Indeed, the analysis shows that up to 90% of the long-run variation in productivity in the post-WWII period is explained by the patent data.

The paper is organized as follows. In section I.B, the existing literature relevant for this analysis is briefly reviewed. Section I.C presents the data and argues for the validity of patent data as a measure of technological progress, while section I.D describes the methodology applied. Section I.E presents the empirical results in the benchmark scenario and in alternative representations of the data. Section I.F analyzes the data when splitting the sample around WWII, and section I.G discusses the implications for

theoretical macroeconomics that the empirical findings imply. Finally, section I.H concludes.

I.B. Existing literature

A substantial literature has focused on developing theoretical models that explain how productivity can be temporarily low after a technology shock. Among these are the models developed by Hornstein and Krusell (1996) and Greenwood and Yorukoglu (1997). Hornstein and Krusell (1996) examine the growth rate of total factor productivity and of labor productivity and show in a model with learning and a compatibility problem that a temporary slowdown in productivity growth can result after technological progress. These results arise in a case where labor is reallocated toward more recent vintages due to a higher rate of technological progress.

Greenwood and Yorukoglu (1997) base their theoretical analysis on the observed decrease in the price of equipment around 1974, indicating technological change, together with an observed increase in wage inequality around the same period. These observations temporally coincide with the measured slowdown in labor productivity growth. Following these observations, Greenwood and Yorukoglu (1997) develop a model where the firm produces at a variety of plants using capital together with both skilled and unskilled labor as inputs. The model shows that an increase in the growth rate of investment-specific technological change leads to higher income inequality during a learning period since skilled labor is relatively higher priced during this period. Furthermore, labor productivity growth slows down since application of the new

technology takes time and because the new technology does not work at full capacity immediately after adoption as a result of the importance of learning.

In empirical studies of productivity growth, Gali (1999) and Francis and Ramey (2004) identify technology shocks through a structural vector autoregression (VAR) using long-run restrictions. Gali (1999) assumes that labor productivity is characterized by a unit root which is driven solely by technology shocks. That is, technology shocks have a permanent effect on productivity and any permanent effects originate solely from these shocks. However, if variables other than technology affect long-run productivity, then the assumption used to identify the technology shocks is violated. Short-run effects based on long-run restrictions might therefore be unreliable. Thus, avoiding this restriction seems important when analyzing temporary short-run effects as done in this paper. Further, if productivity is trend stationary with deterministic breaks, then the long-run restrictions are invalid and can result in misleading conclusions.

To avoid using identifying long-run restrictions an alternative is to compute technology series based on total factor productivity. Basu, Fernald, and Kimball (2006) construct a measure intended to capture aggregate technology. Their technology series is based on aggregate total factor productivity, controlled for varying utilization of capital and labor, non-constant returns and imperfect competition, and aggregation effects. However, total factor productivity remains a residual that likely includes other factors than technology. An alternative approach is therefore to use a direct measure of technological change which is empirically observed. One of the pioneers in using patent statistics as indicators of inventive output was Jacob Schmookler. He examined relations between inventive and economic activity and explored the relation between successful

innovations and capital investment. The study in Schmookler (1972) contains an extensive list of patent statistics.

Several studies in the patent literature have concluded that patent counts do have important information relevant for measuring technological progress and knowledge (Lach (1995), among others). Furthermore, Hall and Trajtenberg (2004) find that highly cited patents are important when identifying periods with diffusion and development of a general purpose technology (GPT)². This is done by exploiting information on the number of patent citations received and in generality measures based on the NBER patent citations data file which is described in Hall, Jaffe, and Trajtenberg (2001).

A big increase in the flow of patents indicates a takeoff of a new technology. This takeoff is then followed by a period of diffusion and adoption of the technology, in which productivity may slow down. Sullivan (1990) examines the widespread patenting and invention during the English industrial revolution. Further, Griliches (1990) has a survey on patents as economic indicators. Jovanovic and Rousseau (2005) provide a careful descriptive analysis of similarities between the Electrification period in the beginning of the 20th century and the IT revolution in the end of the century. They note how patenting should be more intense after the arrival of a GPT. For an in-depth analysis of the Electrification period, see Du Boff (1979) and Devine (1983).

In recent studies, a substantial amount of work has been done on patent data within the area of industrial organization. While the microeconomics literature has exploited this measure of technological progress, it has rarely been applied in the

² A General Purpose Technology (GPT) is described in Hall and Trajtenberg (2004) as a new technology that is extremely pervasive and used in many sectors of the economy and is subject to continuous technical advance after it has first been introduced.

macroeconomic time-series literature in spite of the fact that patent data are a source for direct measures of technology improvements. One macroeconomic paper that does incorporate data on patent statistics is Shea (1998). He employs an annual panel data set containing total factor productivity (TFP), research and development (R&D), and patent applications, sorted by industry and covering the period 1959-1991. He concludes that favorable R&D and patent shocks increase inputs in the short run but do not significantly increase measured TFP. However, grouping patent data at the industry level is associated with many potential problems since there is no clear data distinction between industry of manufacture and industry of use. Furthermore, many historically important inventions have arrived before 1959 and the recent surge in labor productivity in the late 1990s is not included in his sample. The long time-series dimension included in this present paper therefore contains valuable information that should be exploited. Further, since many aggregate variables exist over the time period after 1889, this paper can examine the effects on macroeconomic variables, other than TFP. The analysis in this paper therefore overcomes many of the problems faced by Shea.

In a related paper, Alexopoulos (2006) uses an indicator of technological change based on book publications in the field of technology. Her annual sample period covers 1955-1997. This new data set is interesting in itself. However, many book titles may be published as the technology becomes adopted and the technology indicator may therefore partly reflect the diffusion of products and not strictly the arrival of a new technology. A study based on aggregate patent data using a long sample period therefore adds significantly to the existing literature.

I.C. Data

This paper follows the line of Shea (1998) by using patent data as a measure of technology since patents are a measure of inventive output in the economy. The paper uses patent applications instead of granted patents as the grant lag tends to vary considerably over time (Hall, Jaffe, and Trajtenberg (2001)). Furthermore, the number of patents granted in a given year tends to be correlated with employment activity at the patent office.

Since the NBER patent citation database only contains citations made after 1975 this paper focuses on total annual utility patent applications received by the United States Patent and Trademark Office (USPTO) in the period 1889-2002. The paper focuses on utility patents since these are considered as invention patents by the USPTO.³ This also corresponds to Hall, Jaffe, and Trajtenberg (2001) who include utility patents in the patent citations data file.

For purposes of identifying the economic response of productivity to technology improvements, using patent data offers an advantage over imposing long-run restrictions, because controversial assumptions about which shocks will affect productivity in the long run are not required. However, as mentioned by Shea (1998) there are drawbacks to using patent data. Namely, changes in patent laws can change the incentive to apply for patents, not all inventions are patented, and the importance of specific inventions varies over

³ Other types of patents are plant patents and design patents. Plant patents can be granted to “anyone who has invented or discovered and asexually reproduced any distinct and new variety of plant, including cultivated sports, mutants, hybrids, and newly found seedlings” (USPTO). Design patents refer to a new design of a product. In most years, utility patents account for more than 93% of total patents and the results in the paper are not sensitive to using total patent applications.

time. However, as mentioned in section I.B, patents do contain important information about technological progress.

The number of patents granted is correlated with changes in patenting activity at the USPTO due to variation in budgetary resources over the administrative cycle, leading to budgetary effects in the granting activity. Furthermore, there may be changes at the patent office which lead to changes in the granting rates over time. On the contrary, this paper employs patent applications, which should be less affected by changes in the patenting activity at the USPTO than data on granted patents. As such, it is not necessary to control for variations in patenting activity due to changes at the patent office. However, using patent applications results in the problem that inventions which are not considered sufficiently unique and therefore are not patented are included in the data. For the present analysis, this is not a severe problem since arrival of a new GPT should lead to a surge of patent applications, as explained by Jovanovic and Rousseau (2005). To the extent that interest lies in exploiting the information about changes in economically important technological progress, patent application data do become a good indicator.

Another potential problem with patent data is that patenting can be considered a strategic decision, and some firms may choose to keep their inventions secret rather than patent them. However, Trajtenberg (2000) notes that it is widely believed that these limitations are not too severe and argues that they do not affect trends or variation over time. Because this paper uses the time-series variation in the patent data, these limitations are not important.

For the present analysis it is important to note that patents measure inventions and not innovations⁴. It is very likely that there is a lag between the arrival of a new invention and its full use in the macroeconomy, as shown in figure I-1. Furthermore, if the economy-wide adoption of new technology is sufficiently slow it is possible for the economy to slow down temporarily after the arrival of a new invention; positive effects may not arise until the technology has been sufficiently adopted.

Another argument for using patent data as a measure of technological progress is the importance of news. Ramey (2006) shows how estimates of the effects of government spending shocks change dramatically if the initial anticipation of government spending is not taken into account. For the present paper, where technology shocks are the center of attention, this problem is particularly important, because technology affects the economy through slow diffusion. Considering shocks that have only immediate and positive effect on productivity may potentially exclude very important information about temporary adverse effects of technological progress. Using information from the patent data about the time of invention enables the analysis in this paper to capture the full effects of technology shocks.

As the measure of productivity, the paper uses labor productivity, calculated as output per hour; the historical data come from Kendrick (1961). Details of the data, including other variables used and their sources, are described in the appendix. The natural logarithm is taken of all variables. The logarithm of the flow of total utility patent applications is illustrated in panel A of figure I-2 and the logarithm of labor productivity and labor productivity growth are illustrated in panel B.

⁴ Innovation indicates first use of a given invention.

The paper uses labor productivity instead of total factor productivity (TFP) in order to avoid some of the problems mentioned in Nordhaus (2005). Namely, the inputs of capital services are not observed directly and therefore must be estimated with specific assumptions when calculating TFP. See Nordhaus (2005) and references therein for a further discussion of this issue. As a robustness check, the calculations in this paper were also done with TFP in place of labor productivity. This did not change the conclusions and these results are therefore not reported.

Figure I-3 plots total patent applications together with total patents granted by year. The overall movements in these two series are similar, but the variation in the application-grant lag in some periods leads to a shift in the series on granted patents. For example, the surge of applications in the second half of the 1930s does not show up in the grant series until the first half of the 1940s. Similar shifts in the grant series can be seen in the second half of the 1940s and in the 1950s. Further, during the 1970s we observe a decrease in the number of patents granted while patent applications remained constant. In general, budget cuts at the USPTO lead to fluctuations in the grant series that are not present in the applications series.

Based on the theoretical findings of Greenwood and Yorukoglu (1997), this paper also examines whether wage inequality changes as a result of technological progress. Data on income and wage inequality are taken from Piketty and Saez (2003). They collected annual data from the Internal Revenue Service back to 1913, which signified the beginning of the modern U. S. income tax. Data on income and wage inequality cover the period 1917-1998 and 1927-1998, respectively. The data include the income and

wage shares of total income and wages for the top decile of tax units⁵. The income shares are calculated by dividing the income for a given fractile by total personal income from the National Income Accounts⁶. Wage shares are computed using an equivalent methodology, though linear interpolation is used where a few observations are missing. Piketty and Saez mention that the Tax Reform Act of 1986 and World War II are important for the development of the data series. During World War II, for example, there is a sharp drop in wage shares of the top decile, and this paper controls for this by including dummy variables whenever these variables are included in the estimation.

Figure I-2, panel B illustrates how labor productivity clearly has an upward trend. This may be due to an inherent unit root with drift or to a deterministic trend. Table I-1 presents the results of Augmented Dickey Fuller unit root tests for labor productivity and patent applications under different assumptions for the alternative hypothesis. According to these tests, the paper cannot reject a unit root in productivity or patents in levels. Tests were also performed for unit roots in differences. These tests were all rejected and are not reported here.

If both time-series are integrated of order one, $I(1)$, it is important to test for cointegration in the data. However, cointegration tests for the full sample (not shown) reject the presence of cointegrating vectors when allowing for a linear trend in the data. It can therefore be concluded that a VAR($p-1$) in log differences can be estimated. However, ignoring efficiency considerations, estimation can also be performed as a VAR(p) in levels and results of this estimation are described in section I.E.

⁵ A tax unit is defined as “a married couple living together (with dependents), or a single adult (with dependents), as in the current tax law” (Piketty and Saez (2003)).

⁶ Piketty and Saez (2003) note that this is the standard procedure when computing income inequality measures in historical studies.

An important issue when testing for unit roots is that unit root tests are hard to reject if a coefficient is close to one. It is likely that the patent-productivity system is stationary around a trend. Perron (1989) considered the null hypothesis that a time series has a unit root with possibly nonzero drift against the alternative that the process is trend-stationary. In this specification he showed that one can reject the hypothesis of a unit root for most macroeconomic time-series when the alternative allows for an exogenous break in trend. Following Perron (1989), the exogenous break can in the pre-World War II (pre-WWII) period be estimated as a change in the intercept for the crash in 1929. For the oil price shock in 1973 the break can be estimated as a change in the slope of the time trend. To allow for a Perron-type specification, this paper estimates a number of VARs with different assumptions, including time trends, breaks in trend, and dummy variables whenever necessary. Results of these estimations are reported in section I.E.

True exogenous technology shocks should not be predictable by past observations of productivity. In order to test whether the measure of technology shocks used here satisfies this requirement, this paper presents Granger Causality tests with patents and productivity in table I-2, panel A. The tests are done both in levels and in differences to avoid any inference problems caused by possible unit roots. It can be seen in the table that patents Granger Cause productivity and that the Granger causality does not run in the opposite direction. This, again, argues for the validity of patent data as a measure of exogenous technological progress.

That patent application data despite their noisy component can be used as a measure of the arrival of major inventions can also be seen by examining a few historically known technological advances. Examples from the beginning of the sample

period include the arrival of the first hydro-electric facility in 1894, the discovery of X-rays in 1895, the airplane in 1903 and the radio in 1906, all of which are of great importance for development of future inventions. And all of these inventions were followed by an increase in patent applications. The second half of the 1930s also showed an increase in patent applications. This observation is consistent with Mensch (1975) who found that the years around 1935 were characterized by a large number of basic innovations which were important for further technological development. In more recent years, one of the most important new GPTs was the internet, which arrived in 1991 during a surge in patenting.

An important issue concerning technological progress is the possible endogeneity of new inventions. As an example, R&D expenditures are important for development of new products. However, if the big changes in the flow of patents over the sample period are thought of as arrival of new GPTs, then these may tend to be less correlated with R&D expenditures. As a robustness check, section I.E also includes R&D expenditures in the analysis.

On the contrary, if we consider adoption of new products in the economy, Comin and Hobijn (2004) showed that real GDP per capita is very important for the rate of adoption of a new technology as is the level of schooling. For many products a network effect is also in place. When examining the diffusion curves for different products we therefore observe the well known S-shape as described earlier. Figure I-4 illustrates the S-shaped diffusion curve for aggregate electric power in American manufacturing. Figure I-5 is a graph of how different inventions became adopted by American households. Note that there is a significant lag from the start of the diffusion process till it reaches its

inflection point. Further, there is a lag between the initial date of invention, which for some products can be seen in table I-3, and the start of the diffusion process. This lag tends to be shorter for more recent inventions just as the diffusion evolves at a faster rate. Alm and Cox (1996) address the fact that as the economy evolves, it takes less and less time for new products to become adopted. An example is the internet which was adopted at a rate that exceeded historically observed rates for other GPTs. This faster rate of diffusion in the later period indicates that any observed negative effects after new inventions may be shorter-lived in the second half of the sample than in the first half.

I.D. Methodology

The benchmark model originates from a bivariate VAR with patents and labor productivity. Estimates are computed through a recursively identified structural VAR with patents as the first variable and productivity as the second. This corresponds to the assumption that patents are only affected by productivity with a lag, whereas productivity can respond to contemporaneous changes in patents. Using this ordering allows for productivity adjustments because of changes in expectations of future profitability after news of new inventions.⁷ The unrestricted reduced form VAR can be written as

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \dots + \Phi_p y_{t-p} + \Gamma x_t + \varepsilon_t .$$

Here, y_t is an $n \times 1$ vector of the n endogenous variables in the VAR. As such, y_t contains patents and productivity in the benchmark specification. When the paper allows for other variables to enter the system these variables will appear as the third variable in y_t . x_t is a vector of exogenous variables. ε_t is a vector of error terms, while c is a vector of

⁷ The paper also tried different ordering of the variables. This did not change the overall conclusions.

constants. Φ_i , where $i = 1, \dots, p$, are matrices of coefficients on lagged observations of y_t , and Γ is a matrix of coefficients for the exogenous variables.

Let Ω denote the variance-covariance matrix of the error terms such that $\Omega = E(\varepsilon_t \varepsilon_t') = PP'$, where P is a lower triangular matrix computed by Cholesky factorization. Following Hamilton (1994), let F denote the matrix of coefficient estimates such that

$$F = \begin{pmatrix} \Phi_1 & \Phi_2 & \dots & \Phi_{p-1} & \Phi_p \\ I_n & 0_n & \dots & 0_n & 0_n \\ 0_n & I_n & \dots & 0_n & 0_n \\ 0_n & 0_n & \dots & 0_n & 0_n \\ 0_n & 0_n & \dots & I_n & 0_n \end{pmatrix},$$

where I_n is an $n \times n$ identity matrix and 0_n is an $n \times n$ matrix of zeros. The orthogonalized impulse response functions from a unit shock to y_j s periods into the future can then be written as

$$\frac{\partial \hat{E}(y_{t+s} | y_{1t}, \dots, y_{jt}, y_{t-1}, \dots, y_{t-p})}{\partial y_{jt}} = F_{11}^s P_j \cdot \frac{1}{P_{jj}}, \quad \text{for } s = 1, \dots, h,$$

where F_{11}^s is the first n rows and n columns of F^s , P_j is the j th column of P , and P_{jj} is the (j,j) element of P . Thus, whenever the paper analyzes responses to a shock in a variable, the paper considers a shock to the corresponding orthogonalized error term.⁸ With this specification, the imputed impulse response functions will depict the change in the forecast that occurred as a result of shocking one of the endogenous variables in the system. The impulse response functions will therefore illustrate changes in a variable,

⁸ The impulse response functions are computed based on one standard deviation shocks, corresponding to not dividing by P_{jj} .

relative to the trend the given variable would otherwise have followed had the given variable not experienced a shock. As such, when the paper talks about negative or positive responses of variables to a technology shock, this should be interpreted as revisions in forecasts such that the given variable is forecasted to be below or above the initially forecasted level. That is, a negative response does not necessarily imply an actual fall in the level of the variable but indicates a slowdown relative to the initially forecasted path.

I.E. Empirical evidence

I.E.1 Benchmark specification

In section I.C, the paper found that unit roots cannot be rejected in the productivity and patent data. If it is assumed that these two variables have a unit root, this would argue for estimating the VAR in log differences in order to obtain stationarity. However, since both estimations in log differences and in log levels are consistent, both estimations are performed on the full sample.⁹ The two specifications show impulse response functions that are very similar, and the paper therefore only reports the results as estimated in log levels. As mentioned above, Perron (1989) found that many macroeconomic time-series are stationary around a trend if we allow for a break in trend. The bivariate VAR is therefore also estimated with time trends. Using this specification, the paper follows Perron (1989) and allows for a change in the intercept in 1930 in the

⁹ Estimating in differences in the presence of unit roots is more efficient than estimating in levels. However, the levels estimation is consistent and often preferred to the difference estimation in order to avoid possible misspecification.

beginning of the great depression and for a break in trend in 1973, following the oil shock.¹⁰

To determine the optimal lag-length in the VAR the Akaike Information Criterion (AIC) is estimated. The AIC suggests using $p = 5$ lags when estimating the VAR in levels. However, if the true lag-length is finite, the AIC estimate will not be consistent. See Bhansali (1997) for an analysis of this. To reduce the small sample bias, the paper therefore chooses $p = 4$ lags when estimating the VAR in levels¹¹ and $p = 3$ lags when estimating the VAR in differences.

On figure I-2, panel A, patent data appear to have a break in trend in 1985. This could potentially be due partly to a change in the patent law in 1985 that may have affected the incentive to apply for a patent. The analysis can control for this by including a break in trend in 1985. The impulse response functions that result from a bivariate VAR with patents and productivity after a one standard deviation shock to patents are illustrated in figure I-6 under different specifications. Panel A of figure I-6 shows the responses using a VAR in levels without any time trends or dummies in the regressions. Panels B, C, and D of figure I-6 include time trends with breaks in trend. The responses are plotted together with 2 standard deviation error bands.

In figure I-6, patents respond positively to a patent shock and in specifications where a time trend is included, the trend-stationarity leads to no permanent effects. Productivity temporarily decreases relative to the initially forecasted level after a positive patent shock under all specifications, and productivity slowly converges back to the

¹⁰ See Ramey and Shapiro (1998) for another example of a Perron type time trend.

¹¹ The paper also tried using $p = 5$ lags. This did not change the overall conclusions.

initially forecasted level. This result supports the hypothesis of Hornstein and Krusell (1996) who examined if technology improvements can cause productivity slowdowns. If the response of productivity is examined in the Perron-type specification, including dummies for WWII and the Great Depression, at a horizon longer than 10 years, the response function (not shown) increases insignificantly above the originally forecasted level, indicating that productivity eventually will be positively affected by a technology shock. Furthermore, many researchers prefer to analyze detrended time series data so this paper also estimated the VAR with the full sample of HP-filtered¹² data. The resulting impulse response functions are depicted in figure I-6, panel E. Using HP-filtered data did not change the conclusions of a temporary productivity slowdown. However, the positive effects in this case show up sooner than in the case of a Perron-type specification.

For the following analysis a benchmark model must be selected. The paper chooses to follow Perron (1989) and include a time trend, allowing for breaks. The benchmark specification can therefore be written as

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \dots + \Phi_p y_{t-p} + \alpha \cdot time_t + \beta \cdot D29_t + \gamma \cdot GD_t + \delta \cdot WWII_t + \lambda \cdot time73_t + \varepsilon_t$$

where the notation is as in section I.D. Additionally, $time_t$ is a time trend starting in 1889, and $D29_t$ is a dummy variable such that $D29_t = 1$ for $t > 1929$ and 0 otherwise. GD_t is a dummy variable that takes the value of 1 in 1931-33 in order to account for the Great Depression. $WWII_t$ is a dummy variable such that $WWII_t = 1$ for $t = 1941-45$, and $time73_t$ is a time trend starting in 1973. A break in trend in 1985 is left out because it has little

¹² HP filter denotes the Hodrick-Prescott filter. An HP parameter, λ , of 400 was used.

effect on the standard errors of the regressions and on R^2 .¹³ Furthermore, Kortum and Lerner (1998) examined the surge in patenting after 1985. They examined if this recent increase is a result of changes in patent laws in the U.S., a widening set of technological opportunities, or a change in the management of R&D facilities. They concluded that the recent surge in U.S. domestic patenting is correlated with an increase in patenting abroad by U.S. inventors and is not specific to U.S. patent law changes. This suggests that a surge in discovery and innovation started around 1985 and argues for not including a break in trend in 1985. Instead, the change is left as variation in the flow of patents, resulting from the arrival of new technology.

Piketty and Saez (2003) mention that the Tax Reform Act of 1986 may temporarily have affected income inequality measures as 1987 and 1988 experienced a relatively large gain in inequality with no permanent level effects. The paper therefore includes a dummy for the two years following the Tax Reform Act when income inequality measures are included.

To find support for the argument that technological progress can lead to productivity slowdowns, the response of other variables must be examined. A trivariate VAR is estimated with patents and productivity as the first two variables and a variable D_t as the third variable¹⁴. D_t will represent variables such as real consumption, gross private investment, output, and an index of stock market prices, among others. Only one of these variables enters at a time according to the measure of interest.

¹³ Including a break in trend in 1985 does not change the overall conclusions. In most cases it only further decreases the response of productivity to a shock to patents.

¹⁴ The paper has experimented with other orderings of the variables without altering the conclusions.

The resulting impulse response functions of a shock to patents are shown in Figure I-7. Each row in figure I-7, panel A, indicates a different VAR with a different D_t . The response functions depicted in figure I-7, panel B, are from different trivariate VARs. Labor productivity shows a transitory slowdown after a patent shock, although insignificant at the 5 percent level in the case of output and hours as the third variable. Note that when consumption and hours are included in the analysis, the response of productivity after 6 years is positive, although insignificant at the 5 percent level. This indicates that the new technology does have a positive effect on labor productivity as is expected from theory. However, the time lag until the response is positive is longer than the standard theory would suggest.

Consumption increases after a patent shock. This is consistent with the notion that consumers expect an increase in their future stream of income after the arrival of new technology. In order to smooth consumption, consumers increase consumption immediately. Panel A of figure I-7 also reports the response of real GDP, which decreases temporarily. Correspondingly, the paper finds a large and significant short-run increase in consumption's share of income after a patent shock. This reflects the importance of consumption smoothing after news arrives about new technology. Figure I-7, panel A, also shows the response of output in the private economy. Here it can be observed that private output does not respond significantly.

The response of investment is insignificant and a clear conclusion cannot be made in this case. There is some indication that investment may be increasing in the short run, which is likely if net exports are decreasing. However, if the technology is adopted slowly, it may be that investment only increases over time as productivity increases. This

is further explored in section I.F. If investment does indeed increase in the short run, then an alternative explanation for the positive responses of both consumption and investment could be if patent applications tend to increase during economic expansions. A patent shock could thereby forecast an increase in consumption and investment. However, this does not fit the response of output, and Granger Causality tests in panel B of table I-2 show no indication that consumption and investment Granger Cause the flow of patents. This interpretation therefore does not seem convincing. Another explanation could be that government spending is correlated with the rate of patenting. However, if government expenditures are included in the VAR, ordered first in the system, then government spending does not show a significant reaction to a patent shock (not shown). This explanation, therefore, does not seem to be driving the results.¹⁵

Hours worked show an insignificant response, although indicating that labor input may be reduced in the long run after the arrival of new technology. The finding that labor productivity temporarily decreases corresponds to the result of Fisher (2005), who finds that productivity may decrease after an investment specific technology shock. However, in his analysis this arises as a result of positive responses of both hours and output, with hours showing the strongest response.

When considering income inequality, existing literature (Krusell, Ohanian, Rios-Rull, and Violante (2000), among others) suggests that wage inequality increases after the arrival of new technology as a result of higher demand for skilled labor. Looking at the empirical evidence available from patent data, there is some indication that this

¹⁵ For some orderings there is some indication that government expenditures may show a negative response to a patent shock. Further examination of the relation between government spending and development of new technology is a subject for future research.

phenomenon is present. The wage inequality measure is described by the wage share of the top decile of tax units. Piketty and Saez (2003) indicate that the top percentile of the income distribution is largely influenced by capital income. The impulse response function is therefore estimated based on data for the 90-99th percentile¹⁶. The impulse response function shows that wage inequality increases temporarily after an increase in the flow of patents; however, this result is not statistically significant at a 5 percent level. Using instead a measure of the income share that covers the period 1917-1998, the response corresponds to the one obtained using wage shares. However, when using the income share as a measure of inequality, the temporary increase is significant. The paper therefore finds support for the notion that a learning period is prevalent when adopting a new invention. This result further distinguishes the paper from Shea (1998), who does not explore how income inequality is affected by a technology shock.

When a measure of wage inequality is included in the VAR, the response of productivity is not statistically significant. This could be a result of the change in the sample period, as data on wage inequality are only available beginning in 1927. Differences between the first half and the second half of the sample will be examined in section I.F.

Using the full sample period, the analysis finds that consumption is affected immediately by the arrival of new technology. Similarly, stock prices are expected to respond. Figure I-8 contains the responses associated with the stock price analysis. Since it is uncertain how quickly the market learns about the new technology, this paper

¹⁶ The paper also estimated the response function including the top percentile. This did not change the responses.

experiments with two different measures of stock prices. The impulse responses are based on a trivariate VAR with patents, productivity, and one of the measures of stock prices. Panel A of figure I-8 uses January values of an S&P Composite index (SP1) in order to annualize the data, while panel B is based on June values (SP6). The top rows of the two figures show the responses of productivity and stock prices to a patent shock, while the bottom rows show the responses of productivity and patents to a stock price shock. The importance of comparing responses from a patent and a stock price shock originates from Beaudry and Portier (2006). They suggest that stock price shocks can reveal news about new technology and identify a shock that affects stock prices contemporaneously, but leads to an increase in productivity only with a lag. Since stock prices are assumed to incorporate all available information, changes in stock prices may arise as a forward-looking response to future patent applications.

Comparing the responses of productivity to a patent shock in panels A and B of figure I-8 indicates that the temporary productivity slowdown is not sensitive to including different measures of stock prices in the analysis. In addition, the responses of productivity to a patent and an SP1 shock show the same overall pattern, although the productivity slowdown following an SP1 shock is insignificant. This may indicate similarities in the underlying information inherent in the patent and early stock price data. The impact responses of SP1 and SP6 to a patent shock are positive but insignificant. On the contrary, patents show a positive and significant response three to four years after a stock price shock, and patents respond faster to an SP6 shock than to an SP1 shock. The fact that patents increase after a stock price shock may result from the forward-looking behavior of stock prices, indicating news about the future profitability of new technology.

Alternatively, a stock price increase can free up resources for funding of R&D and thereby lead to a future response of patents. A closer examination of this is left for future research.

I.E.2 Robustness of the results

Many macroeconomists are reluctant to accept patent data as a measure of technological progress because of the noise inherent in the data. As a robustness check, this paper therefore reexamines the impulse responses using different measures of technological progress.

I.E.2.1 The patent stock

A measure of the stock of patent applications is created, following Lach (1995). This corresponds to computing the stock of knowledge in the economy instead of focusing solely on the addition of new technology. Let P_t indicate the flow of patent applications in period t which was used in the previous section. The stock of patents, KP_t , is then estimated as

$$KP_t = \frac{P_t}{\delta + g} \quad t = 1889,$$

$$KP_t = (1 - \delta)KP_{t-1} + P_t \quad t = 1890, \dots, 2002.$$

δ indicates the rate of depreciation of patent capital and is set to 15%, a level that is common in the literature. g is the average growth rate of patent applications over the full sample. The patent stock is illustrated in figure I-9 together with the flow of patents. When comparing the two series, it can be observed that the patent stock mainly differs from the data on the flow of patents by smoothing the series.

The response of productivity after a shock to the stock of patents is shown in figure I-10¹⁷. The impulse response function shows that the temporary negative effect on productivity remains. This result is also robust to changes in the depreciation rate, δ , which was varied in the interval $\delta \in [0, 1]$.

Using the stock of patents as the measure of technology, the analysis finds that consumption responds positively, corresponding to the effect using data on the flow of patents. This response is therefore not shown. Since the results are unchanged when using the stock of patents, the paper chooses to return to the use of patent flows as the measure of technological change.

I.E.2.2 Evidence from a restricted model

The VAR above incorporates dynamics in the system by allowing lags of productivity to affect the flow of patents. However, from table I-2 it can be concluded that productivity does not Granger cause patents. Allowing for these dynamics in the VAR may therefore result in an unnecessary degrees of freedom reduction and less precise parameter estimation. To take this issue into account, the paper follows the approach of Lach and Schankerman (1989), who use firm-level data to estimate the importance of shocks that affect R&D, investment, and the stock market rate of return. Following their procedure, this paper allows investment to help explain the variation in patents and productivity in the unrestricted system of equations. This section therefore allows for three different kinds of shocks to the system.

¹⁷ When the patent stock is used as the measure of technology, the VAR is estimated using $p = 6$ lags as suggested by the AIC criterion. The LR and Hannan-Quinn (HR) criteria suggest using $p = 5$ lags. This does not change the result.

Ignoring exogenous variables, the unrestricted system of equations looks as follows:

$$\begin{bmatrix} p_t \\ y_t \\ i_t \end{bmatrix} = \begin{bmatrix} B_{11}(L) & B_{12}(L) & B_{13}(L) \\ B_{21}(L) & B_{22}(L) & B_{23}(L) \\ B_{31}(L) & B_{32}(L) & B_{33}(L) \end{bmatrix} \begin{bmatrix} p_{t-1} \\ y_{t-1} \\ i_{t-1} \end{bmatrix} + C \begin{bmatrix} \varepsilon_t \\ \eta_t \\ \tau_t \end{bmatrix}$$

where p_t is the flow of patents at time t . y_t indicates productivity, and i_t is investment. $B_{ij}(L)$ for $i, j=1, \dots, 3$ are polynomials in the lag-operator, L . Finally, ε_t , η_t , and τ_t , are orthogonal disturbance terms, where it must be determined how the shocks affect each equation. C is a matrix of coefficients.

Following Lach and Schankerman (1989), this paper uses F-tests, corresponding to Granger Causality tests, as exclusion criteria in the system. The model is estimated equation by equation assuming trend-stationarity with breaks in trend as described earlier, and the F-tests are computed on the individual equations. The following steps test whether patents, productivity, and investment individually and collectively Granger cause each other. The steps can be explained as follows:

Step 1. H_0 : y_t and i_t do not Granger cause p_t , neither individually nor collectively.

Step 2. H_0 : p_t and i_t do not Granger cause y_t , neither individually nor collectively.

Step 3. H_0 : p_t and y_t do not Granger cause i_t , neither individually nor collectively.

Table I-4 shows the results of the tests.

From step 1, the paper concludes that lags of productivity and investment do not help predict current levels of the patent flow, whereas the tests in step 2 show that lags of both patents and productivity do have predictive power for current productivity. For investment, there is evidence that lags of investment are important for prediction.

Furthermore, at the 10 percent level it is rejected that patents and productivity jointly can be dropped from the regression, although neither has explanatory power individually. Since the theoretical prior is that patents help predict investment, the paper chooses to include patents and productivity in the investment equation.

Based on the results of the exclusion restrictions, the paper follows the recursive identification structure used for the VAR in section I.E.1 to restrict the matrix C , such that it is lower triangular. Ignoring the constant and other exogenous variables, the restricted system of equations can then be written as

$$\begin{bmatrix} p_t \\ y_t \\ i_t \end{bmatrix} = \begin{bmatrix} B_{11}(L) & 0 & 0 \\ B_{21}(L) & B_{22}(L) & 0 \\ B_{31}(L) & B_{32}(L) & B_{33}(L) \end{bmatrix} \begin{bmatrix} p_{t-1} \\ y_{t-1} \\ i_{t-1} \end{bmatrix} + \begin{bmatrix} \alpha & 0 & 0 \\ \beta & \delta & 0 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \eta_t \\ \tau_t \end{bmatrix},$$

where effects of the orthogonal disturbances on the endogenous variables are normalized in the i_t -equation, as indicated by the row of ones. The matrix of coefficients on the disturbance terms indicates the causal ordering by being lower triangular such that a shock to patents, ε_t , is allowed to have immediate effect on the remaining endogenous variables. The coefficient estimates of the endogenous variables in the restricted system are shown in table I-5 together with standard errors of the estimates and the variance-covariance matrix of the residuals from the regressions, $\hat{\Sigma}$. It is important to note that the matrix of coefficients on lagged endogenous variables is lower triangular in this restricted system. This means that there is no feedback from changes in productivity to patents as was the case in the benchmark model in section I.E.1.

Since the residuals can be decomposed into orthogonal disturbance terms it is of interest to identify the effects that these orthogonal disturbances have on the endogenous

variables. To do this, the symmetric variance-covariance matrix of the error terms is analytically solved as

$$\Sigma = \begin{bmatrix} \alpha^2 \sigma_\varepsilon^2 & \dots & \dots \\ \alpha\beta\sigma_\varepsilon^2 & \beta^2 \sigma_\varepsilon^2 + \delta^2 \sigma_\eta^2 & \dots \\ \alpha\sigma_\varepsilon^2 & \beta\sigma_\varepsilon^2 + \delta\sigma_\eta^2 & \sigma_\varepsilon^2 + \sigma_\eta^2 + \sigma_\tau^2 \end{bmatrix},$$

where σ_i^2 is the variance of the orthogonal error term i , for $i = \varepsilon, \eta$, and τ .

The 6 distinct elements of the variance-covariance matrix yield a system of 6 equations in 6 unknowns.¹⁸ Solving this system of equations allows the paper to find the coefficients on the shocks and the variances of the disturbances. Parameter estimates are given in table I-6. Impulse response functions from the restricted model are then computed by simulation and shown in figure I-11. It is confirmed that productivity responds negatively to the arrival of new technology as a shock to ε_t , which is the shock associated with the flow of patents, leads to a decrease in productivity. The paper therefore concludes that the results are robust to restricting the system in order to obtain more precise parameter estimates.

I.E.2.3 Research and development

R&D expenditures, which are an input to the production of new technologies, precede any future patents and may lead to inventions that are not patented. It is therefore of interest to see how productivity responds to an R&D shock. For this analysis, the paper uses data on investment in privately financed R&D for the period 1935-1997. The resulting impulse response functions from a trivariate VAR with R&D, patents, and

¹⁸ The 6 unknowns are the three parameters, α , β , and δ , together with the three variances of the orthogonal disturbance terms, σ_ε^2 , σ_η^2 , and σ_τ^2 .

productivity are shown in figure I-12. As theory predicts, the system shows that patents indeed increase significantly after an R&D shock and that productivity responds negatively in the short run. However, an interesting feature of the impulse response of productivity to an R&D shock is the positive effect after around 7 years. This is likely due to leaving out the relatively slow rate of diffusion of products during the Electrification period in the beginning of the 20th century. Using R&D data over the period 1935-1997, when the speed of diffusion tended to be faster, makes it possible to identify the eventual positive effects of new technology on productivity.

That the time period is important can also be seen from the corresponding response of productivity to a patent shock in figure I-12. This figure shows a response similar to what is observed with an R&D shock.¹⁹ The equivalent responses from a bivariate VAR (not shown) with either patents or R&D and productivity for the period 1935-1997 show similar responses. That is, patent data succeed in identifying the initial short-run response and the future positive response. The paper concludes that the results are robust to using different measures of technology.

The observation that VARs, using either R&D data or patent data, produce equivalent impulse responses supports the validity of patent data as a measure of technological progress. However, the fact that impulse response functions based on the sample period 1935-1997 show a different pattern than when based on the full sample indicates the importance of further analysis of sub-samples of the data.

¹⁹ The trivariate VAR was estimated under several different specifications for the ordering of the variables. The resultant responses look similar to the ones illustrated in figure 12 and are therefore not reported.

I.E.2.4 The pre-IT period

One can argue that the increase in the rate of patenting after 1985 explains a large part of the result since productivity growth was relatively low around this period. The estimations were therefore repeated, leaving out the period 1986-2002. This did not change the conclusions but only yielded a further negative response of productivity to a patent shock and consumption still exhibited a temporary increase after a patent shock. However, the initial response of investment was muted and became negative after a few years, matching the negative response of output. Overall, limiting the analysis to the period before the surge in patenting in 1985 and thereby only including the pre-Information Technology (IT) period does not change the conclusions but only renders responses of productivity to technology shocks that are more negative.

The fact that the response of investment is more negative while the data show a longer-lasting slowdown in productivity when considering the pre-IT period may indicate that the faster rates of diffusion in the last part of the 20th century may be very important for understanding and identifying any economic contractionary or expansionary effects of new technology. This is so, because the more negative response of investment in the early period is an indication of slow diffusion where firms postpone investments until the new technology has been further improved. As seen in figure I-5, the rate of adoption of electricity among American households was slower than the equivalent adoption rate for the internet. This paper therefore now considers any possible differences between the pre-WWII and the post-WWII periods.

I.F. Pre- and post-WWII

The sample is now divided into two sub-periods. The pre-WWII period covers the years 1889-1940 while the post-WWII period extends over 1948-2002. Doing this allows technological progress to affect productivity differently during the Electrification period, when the diffusion of technology was relatively slow, than during the IT period, when diffusion happened more rapidly.

The Electrification period was a period over more than 30 years and was a period during which several important GPTs were invented and implemented. Because of the relatively slow rate of diffusion for electricity, it is very likely that learning and reorganization processes within firms were relatively long lasting, leading to more pronounced negative effects on productivity in the pre-WWII period than in the post-WWII period. For the IT period, adoption of the internet started immediately after the invention in 1991 and the speed of diffusion was fast already from the beginning. Therefore, one should expect shorter-lasting negative effects on the macro economy since any positive network externalities will arrive faster with a high rate of diffusion relative to a slow diffusion process.

A further argument for dividing the data into two periods, before and after WWII, is the change in volatility. Figure I-2, panel B, shows how productivity growth exhibited larger volatility in the pre-WWII period where the standard deviation of the growth rate is 0.039, than after WWII, where the standard deviation is merely 0.016. Similarly is it the case for the growth rate in patent applications which also experienced a decrease in the variance after WWII.

I.F.1 VAR estimation on two sample periods

The impulse response functions from a bivariate VAR with patents and productivity in the two sub-samples are shown in figure I-13. For both the pre- and the post-WWII periods the AIC suggests using $p = 1$ lag. However, because of the slow diffusion of technology during the early period, more lags may be needed. The figure therefore also shows the response functions using 4 lags. As seen, the response functions are robust to using different lag lengths.

The difference between the two periods is easily seen. In the pre-war period, productivity depicts the temporary slowdown as seen when using the full sample. On the contrary, in the post-war period, there is no evidence of a temporary slowdown. Instead, the positive effects of a technology shock are now prevalent such that productivity increases significantly after 2-3 years. Including more lags in the estimation postpones the significantly positive effect another couple of years but without evidence of a productivity slowdown. This result is very important for understanding the productivity slowdown during the Electrification period and after 1973. The paper finds evidence that technology, indeed, can lead to a temporary productivity slowdown as seen in the early period. However, from this analysis it can be concluded that the productivity slowdown after 1973 does not seem to be a result of the arrival of new technology.

In panel A of figure I-13 with pre-WWII data, the long-run positive effects of technological progress on productivity do not show up when using 1 or 4 lags. This may be due to only considering a sub-sample period when diffusion was considerably slow. Figure I-13, panel A, therefore also estimates the VAR using 9 lags. This consumes many degrees of freedom but may provide an indication that the long diffusion lags are

important. Indeed, when including more than 8 lags the future positive effects do show up in the long run, although insignificantly, while still depicting a temporary slowdown in the short run.

For the pre-WWII period, responses of other variables than productivity look similar to the responses using the entire sample period and are therefore not reported. For the post-WWII period there are important differences that must be further analyzed. The following therefore focuses on the post-WWII period which can yield important insights for the current literature.

I.F.2 Post-WWII VECM

If there is evidence of cointegrating relationships when considering the post-WWII period separately, a vector error-correction model (VECM) may provide a better description of the data than stationarity around a deterministic trend with breaks. Furthermore, the inclusion of a break in trend in the regressions may partly explain the lack of a productivity slowdown in the later period. It is therefore of interest to examine the system of equations without exogenously removing the 1973 trend break.

When looking at the full sample period and at the pre-WWII period only, there is no evidence of cointegration and the results are robust to different specifications. However, cointegrating relationships for the post-WWII period cannot be rejected at a 5 percent level. Results from a cointegration test in the bivariate system for this period are reported in panel A of table I-7 and panel B reports corresponding tests in trivariate systems. At a 5 percent level, the paper cannot reject one cointegrating relationship in the system. This section therefore examines the responses to a patent shock under the

assumption that a VECM best describes the post-WWII data. Impulse response functions with 95 percent confidence intervals calculated by Hall Bootstrap²⁰ methods are reported in figure I-14. Panel A of this figure illustrates the responses of patents and productivity to a patent shock in a bivariate VECM. Each row in panel B depicts responses to a patent shock, based on a VECM with three variables where the third variable changes, according to the measure of interest. Lag length is determined mainly based on AIC estimates. The corresponding VARs without imposing cointegrating relations and without deterministic trends in the regressions are also estimated in figure I-15.²¹

Figure I-15, panel A, reports the impulse response functions from a bivariate VAR with patents and productivity. Panel B of figure I-15 reports the equivalent responses from trivariate VARs. The organization of the variables corresponds to the ordering from the VECM analysis. The responses for productivity, consumption, investment, and output, as measured by GDP, generally show equivalent pictures whether estimated from a VECM or a VAR.

Figure I-14, panel A, with VECM results reports that labor productivity does not display a significant slowdown after a patent shock but that productivity increases significantly after several years. In figure I-14, panel B, consumption increases slowly but the response remains statistically indistinguishable from zero at a 5 percent level. However, the corresponding VAR with no cointegration in figure I-15, panel B, does depict a significant response. Investment and output slowly converge to a significantly higher level. When based on a VECM, hours do not show a significant response but do

²⁰ Efron bootstrap confidence intervals were also computed. Hall confidence intervals tend to show more significant results than Efron estimates. However, the overall conclusions derived from impulse response functions using these confidence intervals were unchanged.

²¹ Impulse responses with trend and break (not shown) depict responses that lead to unchanged conclusions.

indicate that labor input use is reduced in the long run after the arrival of new technology. However, when estimating the response of hours based on a VAR with no cointegration, as illustrated in panel B of figure I-15, hours do not demonstrate a reduction in input use in the long run. If hours are truly constant, such that long-run labor input use is unchanged after the arrival of new technology, then the post-WWII impulse response functions can be matched by a standard growth model with labor held constant, assuming that technology arrives exogenously through slow diffusion. The theoretical implications will be discussed in section I.G.

The VECM analysis confirms results from the previous section, that there is not evidence of a significant slowdown in the post-WWII period after the arrival of new technology. That any transitory contractionary effects of a new invention are more prevalent in the pre-war period indicates the importance of further analysis of the consequence of the rate of diffusion and learning for the economic effects. It is left for future research to explore these differences in more thorough detail. Instead, the paper now estimates the importance of technology shocks for variations in productivity at different horizons.

I.F.3 Variance decomposition

In the neoclassical models, a large focus has been put on the role of technological progress. Using the historical data in this paper, it is possible to estimate the importance of a patent shock for the variation in productivity. Table I-8, panel A, shows the results from a decomposition of the forecast error variance during the two sub-sample periods under different assumptions about the data in a bivariate analysis with patents and

productivity. Panel B of table I-8 reports results using R&D as a measure of technology instead of patents and panel C displays the results if a third variable is included in the system.

In the period 1889-1940, 37 percent of the variation in productivity can be explained by the patent shock at a 50 year horizon. Similarly, in the post-WWII period 61.5 percent of the variation is explained by the technology shock when estimating in a VAR with deterministic trend assumptions but almost 90 percent is explained when taking into account possible cointegration during the sample period. These numbers indicate that patents explain a large fraction of long-run variation in productivity and that patent data therefore do capture the arrival of new technology. As a result, the paper concludes that technology shocks, indeed, are important for fluctuations in productivity. Equivalently, R&D explains around 27 percent of the variation in productivity. However, in the case of R&D, the sample period includes the war time years.

Generally, technology shocks, identified with patents, seem to explain a larger fraction of the variance of productivity in the post-war period than in the earlier period. However, the estimates in table I-8 are smaller than the results computed by Francis and Ramey (2004). Through a long-run specification, they find that technology shocks explain more than 90 percent of the variance of productivity on a horizon longer than three years. That patents only account for up to 90 percent of the forecast error variance of productivity at a horizon of 50 years is an indication that also other sources than technology are important for explaining long-run fluctuations in productivity. It is therefore likely that human capital can be important, also in the long run, when explaining fluctuations in productivity growth.

Many economists focus mainly on determining the effects of new technology on productivity at a business cycle horizon. As an example, Beaudry and Portier (2006) have argued that news about future technology can lead to an economic expansion in the short run. However, the variance decomposition in table I-8 illustrates that the arrival of new technology as measured by new patent applications only have little importance for the variation in productivity at a horizon shorter than three years. After five years, approximately 24 percent of the variation in productivity is explained by patents in the pre-WWII period while around 18 percent of the variation is explained in the post-WWII period when estimating with a VAR.

To further explore the importance of technology shocks at the business cycle horizon, table I-8, panel C, reports the variance decomposition results for the post-WWII period when based on a trivariate system. The table shows that technology shocks alone are not important for explaining business cycle fluctuations since less than seven percent of the variation is explained by patents at a horizon shorter than five years. However, technology is important for explaining variations in investment and output in the long run. Furthermore, when consumption, output, or hours worked are included in the system, the variation in productivity explained by patents at a horizon of 50 years remains around 90 percent when estimated by a VECM (not shown) and the overall conclusions are not sensitive to the ordering of the variables in the systems.

I.G. Theoretical implications of the results

The main purpose of this paper is to provide empirical, statistical evidence for how the economy responds to the arrival of new technology. However, the result that

technology shocks are not important for explaining business cycle expansions has important implications for current theoretical macroeconomic research. The real business cycle model predicts that a technology shock has an immediate and positive impact on the economy. However, from the present analysis, this paper concludes that this result does not match the data. The next important step is therefore to explore which models can explain these empirical findings.

The post-WWII response functions point in the direction of incorporating slow diffusion when modeling technological progress. A model with a continuum of plants that adopt the new technology at different times is therefore an appropriate setting for incorporating slow diffusion. Rotemberg (2003) has a model which incorporates the diffusion of technological innovations that can lead to temporary slowdowns in output. However, this coincides with fluctuations in hours worked that do not correspond to the present empirical findings. Therefore, an S-shaped adoption rate cannot alone explain the empirical results.

The pre-WWII period is not only affected by slow diffusion but also by temporary adverse effects that significantly decrease labor productivity. One promising line of research is therefore to explore the importance of learning and the influence of the stock of human capital that may facilitate the adoption of new technology. On this issue, Bartel (1989) showed that large businesses that are introducing new technologies are more likely to have formal training programs and that formal training of workers have a positive impact on productivity. Therefore, more skilled labor in the post-1948 period compared to the early part of the sample may enable easier and faster learning and thereby shorten the time-lag until any positive effects show up in the productivity data.

This is also evidenced by Bartel and Sicherman (1999) who confirm that workers in industries with higher rates of technological change have more human capital. Compatibility problems between old and new technologies may also play a role in the early part of the sample and including such factors may improve the performance of a theoretical model explaining the effects of technological progress on productivity over long sample periods.

I.H. Conclusion

This paper has argued that patent application data can be used as a valid measure of technological progress. Using vector autoregressions on data from 1889 to 2002, this paper concludes that when examining the full sample period aggregate labor productivity responds negatively in the short run after technological progress occurs. This result is robust to several different methodological specifications and to utilizing the stock of patent applications and R&D data as alternative measures of technology.

The paper found evidence that the effects of technology shocks on productivity have changed substantially over the last century. This may be a result of changes in the rate of diffusion of technology since diffusion has been faster in the post-WWII period than it was in the pre-WWII era. A faster rate of diffusion can lead to shorter-lasting negative effects of technology shocks, and future positive effects on productivity will then show up in the impulse response functions. The effect of human capital may also be very important since more skilled labor facilitates the adoption of new technology. That there are important changes over the sample period is indeed what the data demonstrate. Using data from 1889-1940, productivity is estimated to be lower than the initially

forecasted level following a technology shock, after which it slowly reverts back to the initial forecast and a further increase. On the contrary, data on 1948-2002 do not show significant negative effects on productivity. Instead, significantly positive revisions in the forecast are observed. Similarly, investment and output follow a path equivalent to that of productivity. Further examination of the importance of the rate of diffusion and the amount of skilled labor for the response of labor productivity to a technology shock is a subject for future research.

Variance decompositions support the role of patent statistics as a measure of technological progress since variations in long-run productivity are explained mainly by patents. However, the analysis also shows that technology shocks are not very important in explaining business cycle fluctuations. The empirical findings in this paper therefore have important theoretical implications. The results point toward the importance of incorporating slow diffusion, human capital, and learning in macroeconomic models when trying to understand the effects of technological progress on productivity.

I.I. Tables and figures

Table I-1: Augmented Dickey Fuller unit root tests

	Alternative hypothesis	
	Constant term, no time trend	Constant term, linear time trend
Patents	1.193202	-0.043288
Productivity	0.069758	-1.678276

Note: 4 lags are used. Variables are in log-levels over the full sample, 1889-2002.

MacKinnon 5% and 10% critical values for rejection of the null of a unit root are -2.8879 and -2.5807, respectively for case 1 with an intercept but no trend included. When a constant term and a linear trend are included, the critical values are -3.4512 and -3.1507, respectively.

Table I-2: Granger causality tests

Null hypothesis		
	F-stat	P-value
Panel A		
Productivity does not Granger cause patents (levels)	0.77926	0.54122
Patents do not Granger cause productivity (levels)	5.18307	0.00077*
Productivity does not Granger cause patents (differences)	0.73067	0.53600
Patents do not Granger cause productivity (differences)	6.50808	0.00045*
Panel B		
Consumption does not Granger cause patents (levels)	0.48862	0.74406
Patents do not Granger cause consumption (levels)	2.14049	0.08123
Investment does not Granger cause patents (levels)	0.61309	0.65417
Patents do not Granger cause investment (levels)	0.75838	0.55478

Note: 4 lags are used when testing in levels. 3 lags are used when testing in differences.

*Rejected on a 1% level.

Table I-3: Great inventions

Year	Product
1894	First hydro-electric facility at Niagara Falls*
1895	X-rays discovered by Wilhelm Roentgen*** Diesel locomotive invented****
1903	Airplane**. Steam turbine generator***
1905	Patenting of alloy of nickel and chromium, Nichrome, making electric toasters possible***
1906	Radio**
1926	Television**
1927	Polyvinyl chloride (PVC)***
1933	Polyethylene****
1934	Diesel locomotive and radar innovated ****
1945	Atomic bombs dropped in Japan***
1953	Microwave oven**
1971	Intel introduces the microprocessor***
1975	Bill Gates and Paul Allen found Microsoft****
1981	IBM introduces the PC***
1983	Cell phone** Apple Computer introduces the Macintosh computer*** Microsoft releases Microsoft Windows 1.0***
1991	Internet**

Source: *Jovanovic and Rousseau (2005).

**Alm and Cox (1996).

***National Academy of Engineering.

****Mench (1975), pp. 127-128, table 4-4.

Table I-4: Exclusion tests in a restricted model

	Null hypothesis	F-statistic	P-value
Step 1 (p_t)	p_t does not Granger Cause p_t	54.02592	0.000000
Step 1 (y_t)	y_t does not Granger Cause p_t	1.236390	0.300998
Step 1 (i_t)	i_t does not Granger Cause p_t	1.910400	0.115306
Step 1 (y_t and i_t)	y_t and i_t do not Granger Cause p_t	1.367494	0.221240
Step 2 (p_t)	p_t does not Granger Cause y_t	3.544856	0.009778
Step 2 (y_t)	y_t does not Granger Cause y_t	42.12399	0.000000
Step 2 (i_t)	i_t does not Granger Cause y_t	0.581868	0.676527
Step 2 (p_t and i_t)	i_t and p_t do not Granger Cause y_t	2.544901	0.014986
Step 3 (p_t)	p_t does not Granger Cause i_t	0.881667	0.478175
Step 3 (y_t)	y_t does not Granger Cause i_t	1.201055	0.315762
Step 3 (i_t)	i_t does not Granger Cause i_t	5.888828	0.000290
Step 3 (p_t and y_t)	p_t and y_t do not Granger Cause i_t	1.939921	0.063181

Note: 4 lags are used. A time trend, a change in the intercept in 1930, a break in trend in 1973, and dummies for the Great Depression and WWII are included.

Table I-5: Coefficient estimates of the restricted model

Variable	Patents	Productivity	Investment
P(-1)	1.006301** (0.096138)	-0.064572* (0.034109)	0.304491 (0.274178)
P(-2)	-0.118558 (0.137876)	0.055203 (0.048012)	-0.419511 (0.385404)
P(-3)	-0.200454 (0.136704)	-0.104881** (0.047861)	0.295276 (0.388206)
P(-4)	0.193563** (0.094011)	0.120116** (0.033607)	-0.323420 (0.279470)
Y(-1)	-	0.517956** (0.090733)	0.796636 (0.760687)
Y(-2)	-	0.185034* (0.102279)	-0.249734 (0.846228)
Y(-3)	-	0.308067** (0.100219)	0.194143 (0.825519)
Y(-4)	-	-0.111920 (0.085658)	0.388071 (0.730636)
I(-1)	-	-	0.398163** (0.107580)
I(-2)	-	-	0.004190 (0.119179)
I(-3)	-	-	-0.087063 (0.110917)
I(-4)	-	-	0.063423 (0.090265)

$$\hat{\Sigma} = \begin{bmatrix} 0.0047 & \dots & \dots \\ 0.0001 & 0.0005 & \dots \\ 0.0012 & 0.0017 & 0.0302 \end{bmatrix}$$

Note: Constants and time trends with breaks, as described in the text, were included in the regressions. Standard errors in parentheses.

(**) Denotes significance at the 5% level.

(*) Denotes significance at the 10% level.

Table I-6: Parameter estimates for the restricted model

Parameter	Value	Parameter	Value
α	3.9167	σ_{ε}^2	0.0003
β	0.0833	σ_{η}^2	0.0056
δ	0.2973	σ_{τ}^2	0.0243

Table I-7: Cointegration in post-WWII data

Hypothesized number of cointegrating relations	Trace Statistic	5 percent critical value	1 percent critical value
Panel A. Bivariate system			
Patents and Productivity:			
0	22.57	15.41	20.04
At most 1	3.53	3.76	6.65
Panel B. Trivariate systems			
Consumption:			
0	36.06	29.68	35.65
At most 1	9.56	15.41	20.04
Investment:			
0	35.13	29.68	35.65
At most 1	15.34	15.41	20.04
Output:			
0	36.21	29.68	35.65
At most 1	8.38	15.41	20.04
Hours:			
0	34.94	29.68	35.65
At most 1	8.41	15.41	20.04

Note: The test allows for a linear deterministic trend in data. 1 lag in differences is included. The paper only shows results for up to 1 cointegrating relation since this is accepted.

Table I-8: Variance decomposition, continued on next page**Panel A. VAR with patents and productivity**

Year	1889-1940 (VAR)		1948-2002 (VAR)		1948-2002 (VECM)	
	Patents	Productivity	Patents	Productivity	Patents	Productivity
1	0.0000	0.2128	0.0000	0.4461	0.0000	0.2214
2	0.4271	2.3610	0.7884	3.5887	0.3083	0.6125
3	0.3661	2.7362	1.8375	8.2642	0.3297	0.5604
5	0.4914	23.8217	3.6410	18.4600	0.2856	4.1188
10	0.9458	33.6160	5.9150	36.3111	0.1731	29.8711
20	1.2758	36.8177	7.2418	51.1076	0.2511	68.0240
50	1.2914	36.9073	7.9620	61.5152	0.9252	89.8874

Note: Columns for “patents” indicate the percentage of the forecast error variance for patents explained by productivity. Similarly, the percentage of forecast error variance for productivity explained by patents is indicated under columns labeled “productivity”. Year 1 is the time of the shock.

1889-1940 includes a time trend, a change in intercept in 1930 and a dummy for the Great Depression. 4 lags are used. 1948-2002 includes a time trend and a break in trend in 1973 in the case of VAR. The VAR employs 1 lag. Including 2 lags only increases the fraction of the variation in productivity explained by patents. In the case of VECM, no break in trend is included and 1 lag in differences is used.

Panel B. VAR with R&D and productivity

Year	1935-1997	
	R&D	Productivity
1	0.0000	0.3337
2	1.1559	0.3999
3	0.8784	5.4773
5	2.5449	16.9040
10	6.2682	25.2598
20	6.9241	27.1433
50	6.9924	27.3293

Note: Based on a bivariate VAR with R&D and productivity. 4 lags included together with a trend and a break in trend in 1973. The column for “R&D” indicates the percentage of the forecast error variance for research and development explained by productivity. Similarly, the percentage of the forecast error variance for productivity explained by R&D is indicated under the column labeled “productivity”. Year 1 is the time of the shock.

Table I-8 (continued): Variance decomposition
Panel C. VAR with patents, productivity, and a third variable

Year	1948-2002 (VAR)				1948-2002 (VECM)			
	C	I	Y	H	C	I	Y	H
1	0.9553	0.0287	0.6880	0.0462	1.1842	1.1876	0.0111	0.0070
2	1.0160	0.2402	0.6965	1.4168	0.8943	2.1753	0.4471	0.8798
3	1.3657	1.0359	1.4694	2.4789	0.8290	3.4458	0.5286	2.9929
5	3.1418	4.4170	6.6761	2.7745	1.2287	6.6531	0.9606	5.6318
10	10.9690	14.4791	19.7172	3.0942	3.5132	16.2715	8.6216	10.6952
20	19.8131	27.1267	30.7217	3.3264	8.4499	32.3941	31.4676	17.4414
50	24.3104	41.4140	41.0630	3.6470	15.6607	54.1356	60.1973	24.9481

Note: The columns indicate the percentage of the forecast error variance explained by patents. Year 1 is the time of the shock. Based on a trivariate system with patents, productivity, and a third variable as indicated in the table.

1948-2002 (VAR) includes a time trend and a break in trend in 1973. The VAR employs 1 lag. In the case of VECM, no break in trend is included and 1 lag in differences is used for C, Y, and H. 0 lags in differences are used when I is included, following the AIC choice.

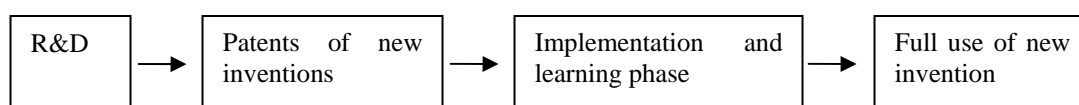
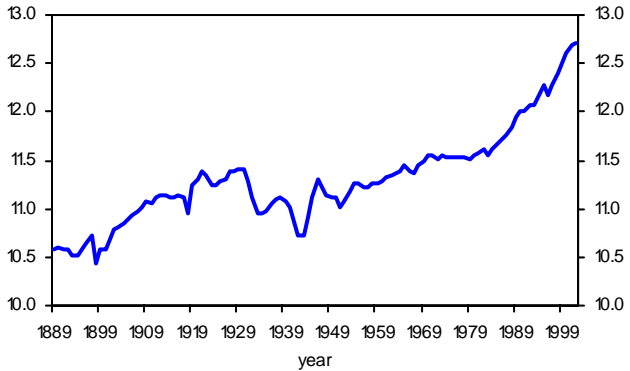


Figure I-1: The flow of technologies

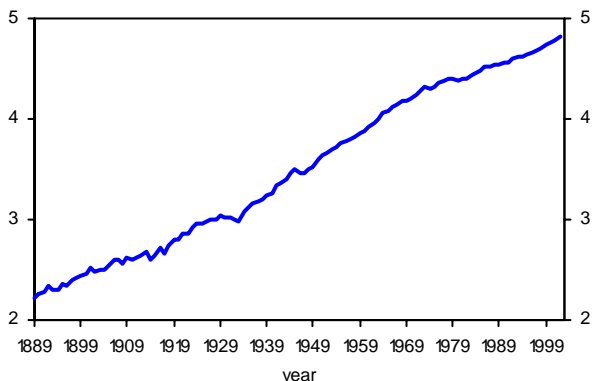
Panel A. Total Utility Patent Applications

Natural Logarithm of Number of Patents



Panel B. Private Business Labor Productivity and Productivity Growth

Natural Logarithm of Labor Productivity



Labor Productivity Growth

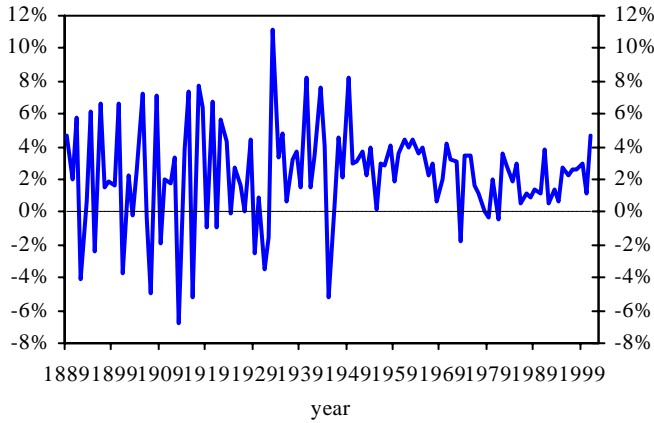
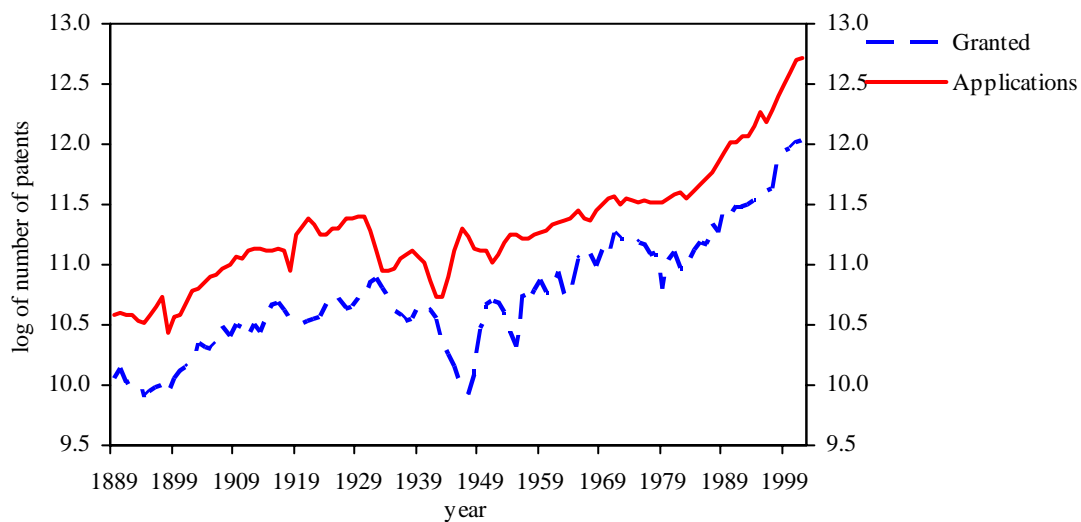
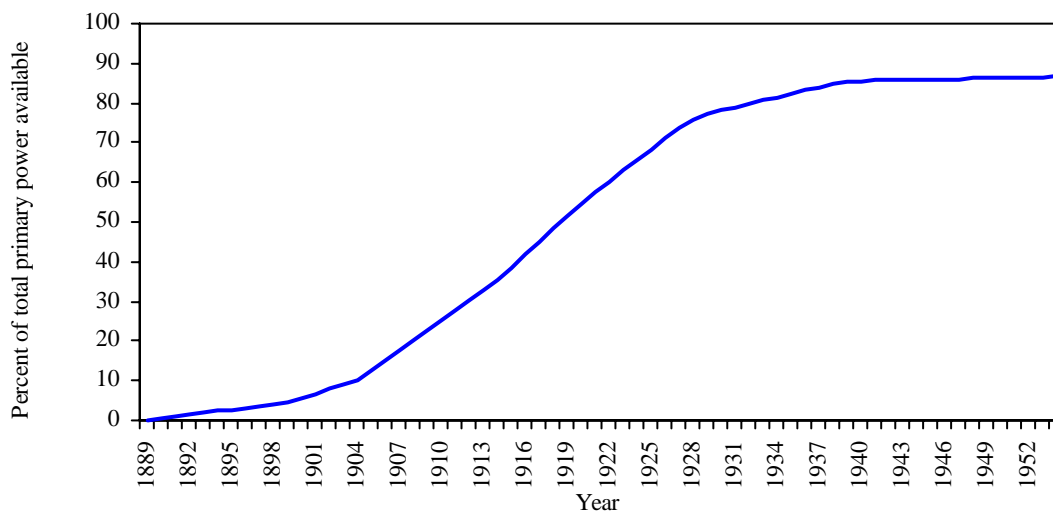


Figure I-2. Patents and productivity



Note: Patent applications are sorted by application year. Patents granted are sorted by grant year.

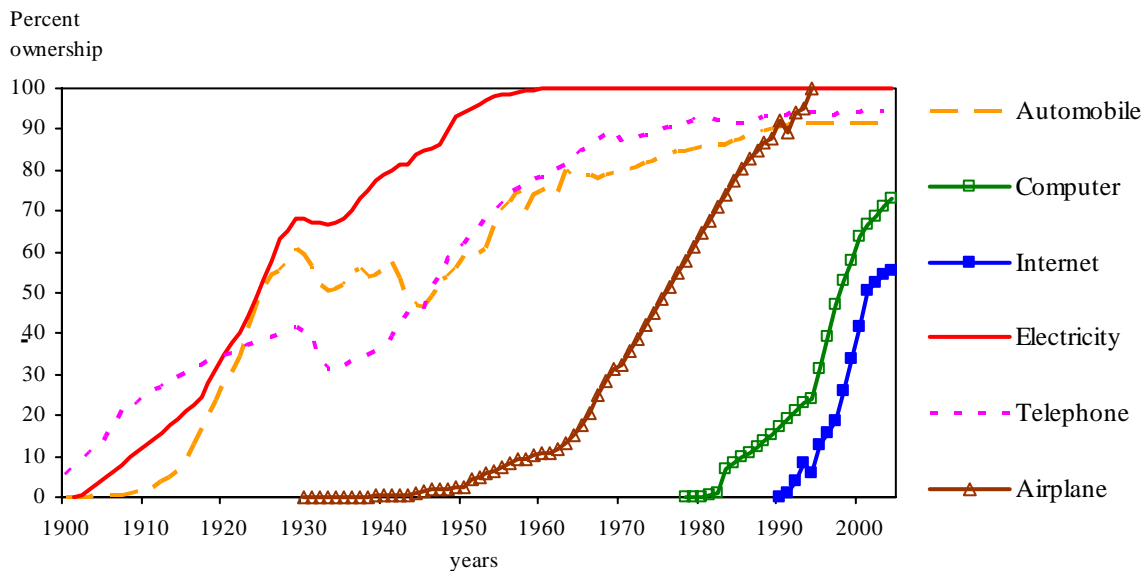
Figure I-3: Total patent applications and patents granted



Source: Du Boff (1979) and author's calculations.

Note: Aggregate electric power is the sum of primary electric motors and the proportion of total primary power engaged in producing electricity for intra-plant use. Linear interpolation is used in place of missing observations.

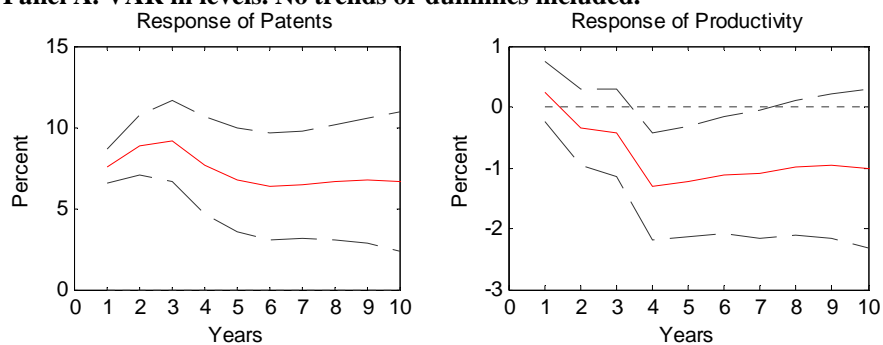
Figure I-4: Diffusion of aggregate electric power in manufacturing



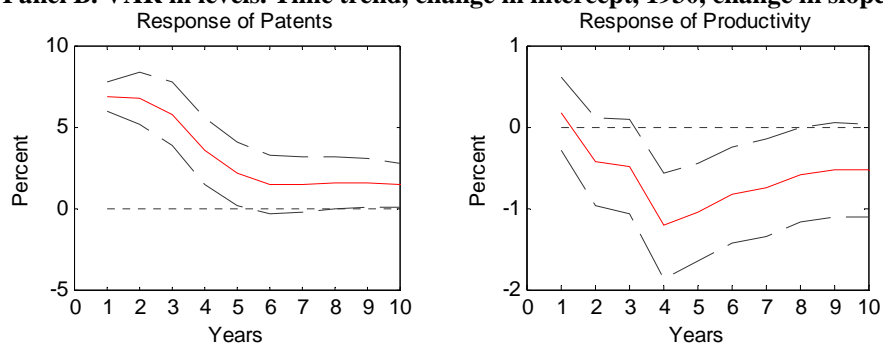
Source: W. Michael Cox, Federal Reserve Bank of Dallas.
Note: Airplane is percentage of air miles traveled per capita relative to miles traveled in 1996. Automobile refers to the number of motor vehicles relative to persons age 16 and older. For further explanation, see Alm and Cox (1996).

Figure I-5: Spread of products into American households

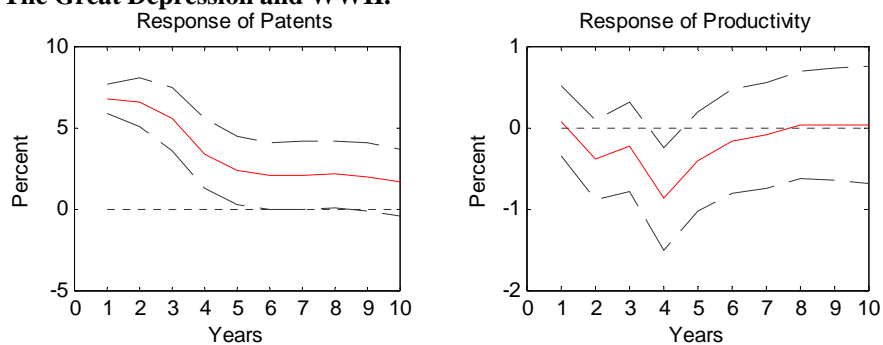
Panel A. VAR in levels. No trends or dummies included.



Panel B. VAR in levels. Time trend, change in intercept, 1930, change in slope, 1973.



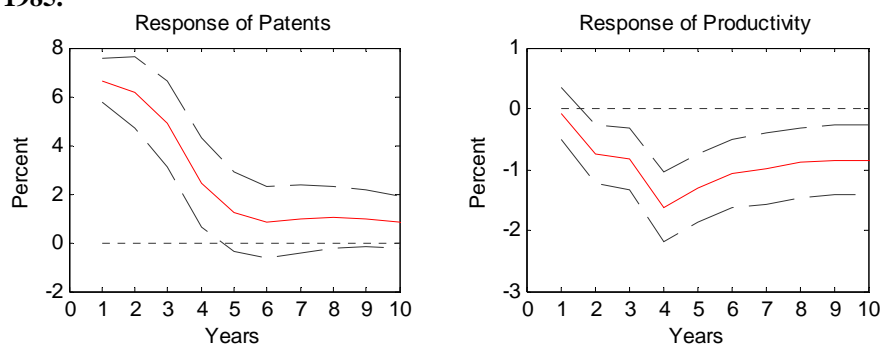
Panel C. VAR in levels. Time trend, change in intercept, 1930, change in slope, 1973, dummies for The Great Depression and WWII.



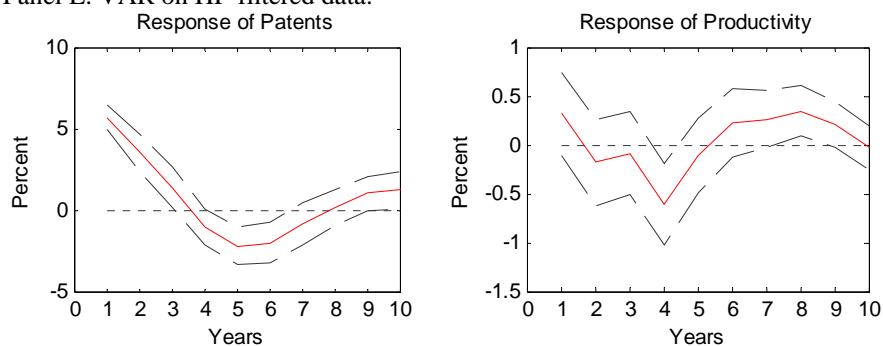
Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line.

Figure I-6: Responses of patents and productivity to a patent shock, 1889-2002, continued on next page

Panel D. VAR in levels. Time trend, change in intercept, 1930, change in slope, 1973, change in slope, 1985.



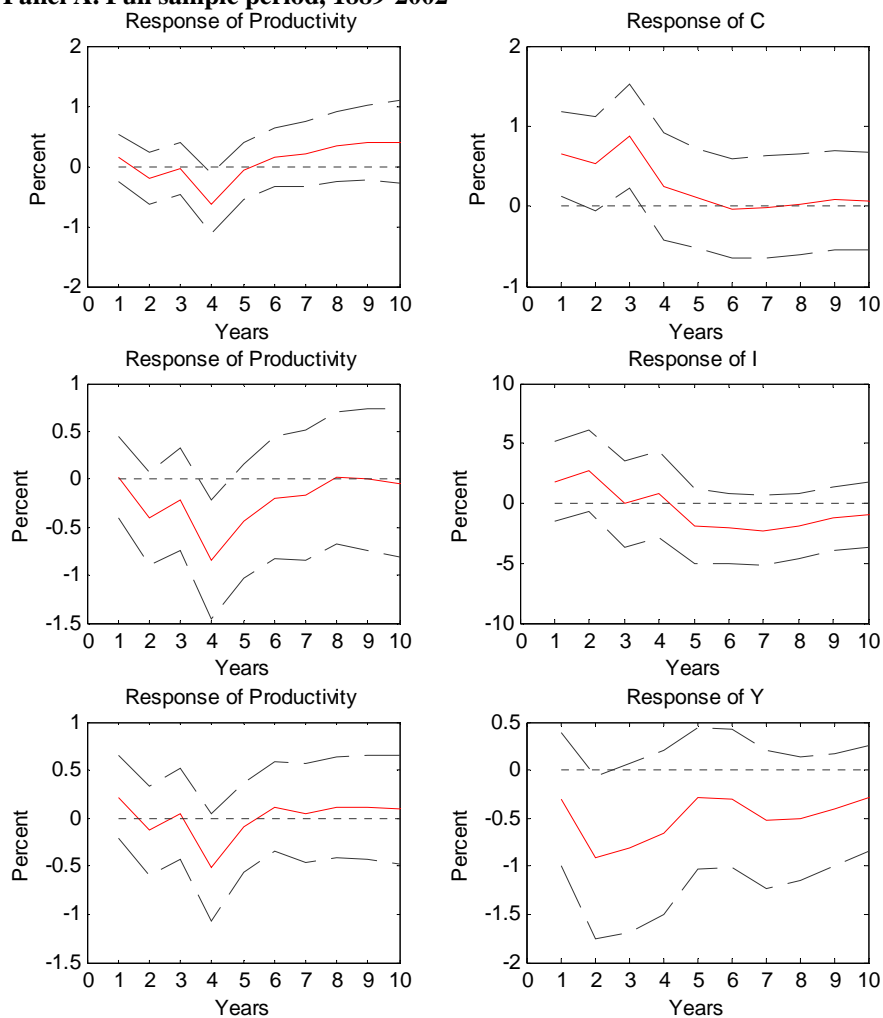
Panel E. VAR on HP-filtered data.



Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line.

Figure I-6 (continued): Responses of patents and productivity to a patent shock, 1889-2002

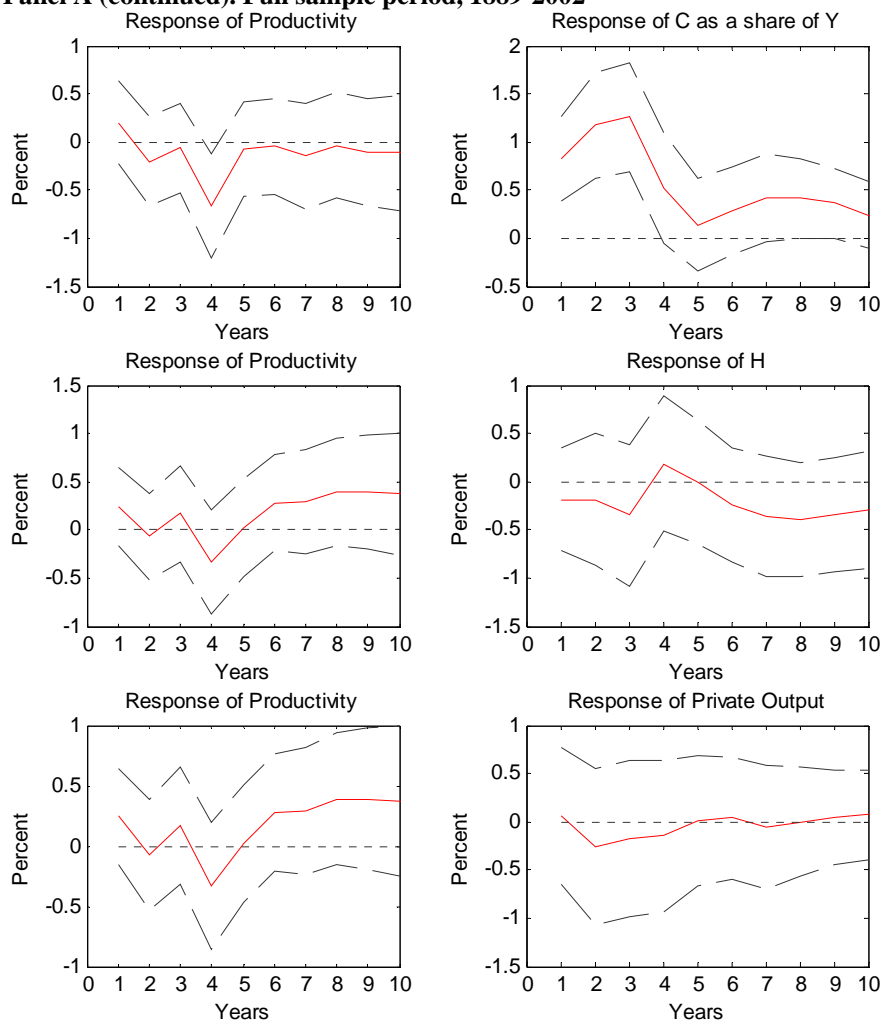
Panel A. Full sample period, 1889-2002



Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line. Each row of responses comes from a trivariate VAR where the third variable is as indicated by the right hand column. A time trend with break in trend in 1973, a change in intercept in 1930, and dummies for The Great Depression and WWII are included in the estimation. Notation is as follows: C = consumption, I = investment, and Y = real GDP = output.

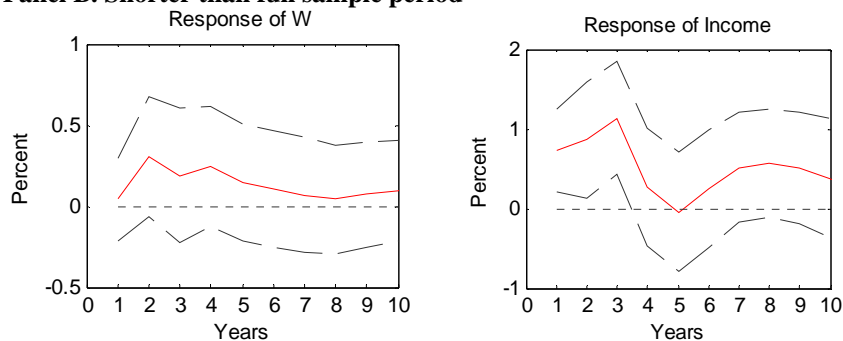
Figure I-7: Responses to a patent shock, continued on next two pages

Panel A (continued). Full sample period, 1889-2002

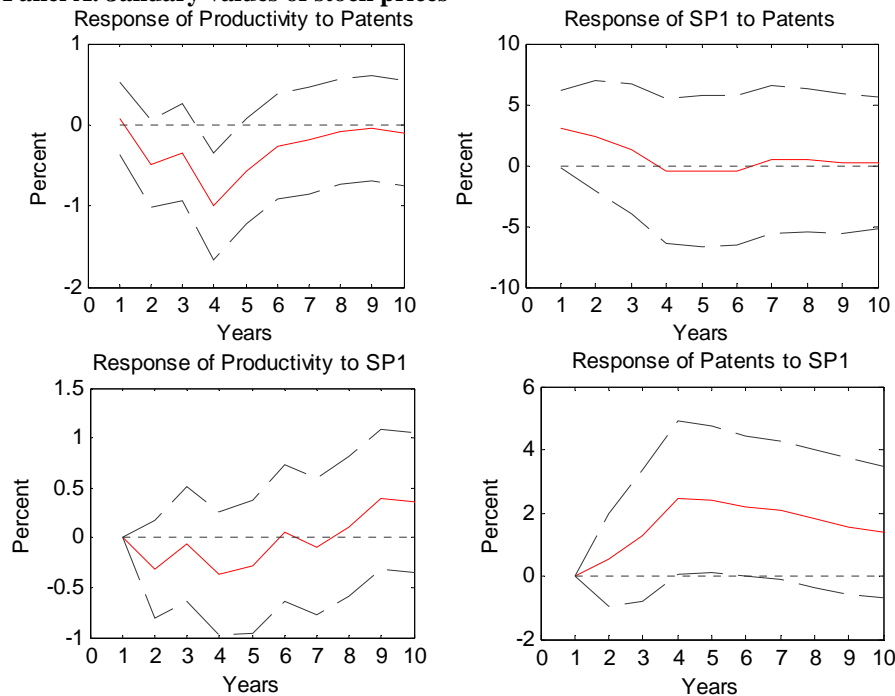


Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line. Each row of responses comes from a trivariate VAR where the third variable is as indicated by the right hand column. A time trend with break in trend in 1973, a change in intercept in 1930, and dummies for The Great Depression and WWII are included in the estimation. H denotes hours worked.

Figure I-7 (continued): Responses to a patent shock

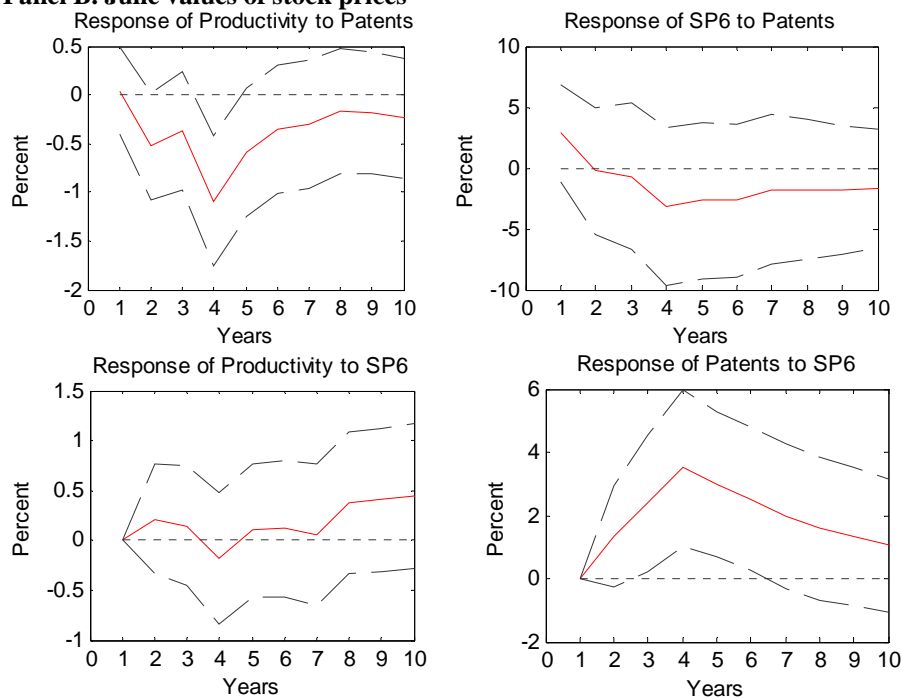
Panel B. Shorter than full sample period

Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line. The response functions are from two different trivariate VARs. Data for wage inequality (W) cover the period 1927-1998. 4 lags are used. A time trend with break in trend is included together with dummies for WWII and 1987-88 and a change in intercept in 1945. Income inequality (Income) covers the period 1917-1998. 4 lags are used. A time trend with break in trend is included together with dummies for the Great Depression, WWII, and 1987-88 and changes in intercept in 1930 and 1945.

Figure I-7 (continued): Responses to a patent shock**Panel A. January values of stock prices**

Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line. The responses are from a VAR with patents, productivity, and stock prices. A time trend with break in trend in 1973, a change in intercept in 1930, and dummies for The Great Depression and WWII are included in the estimation. SP1 denotes January values of the stock price index.

Figure I-8: Stock prices, 1889-2002, continued on next page

Panel B. June values of stock prices

Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line. The responses are from a VAR with patents, productivity, and stock prices. A time trend with break in trend in 1973, a change in intercept in 1930, and dummies for The Great Depression and WWII are included in the estimation. SP6 denotes June values of the stock price index.

Figure I-8 (continued): Stock prices, 1889-2002

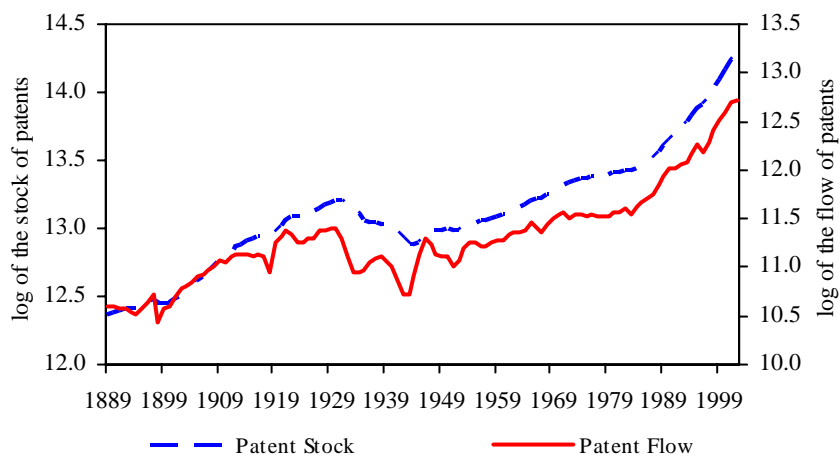
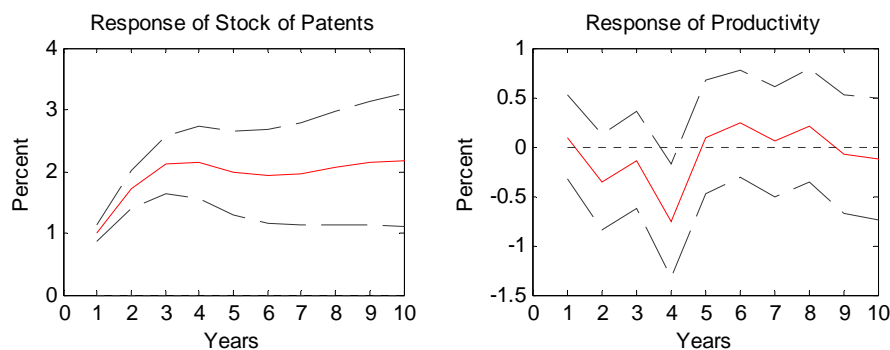
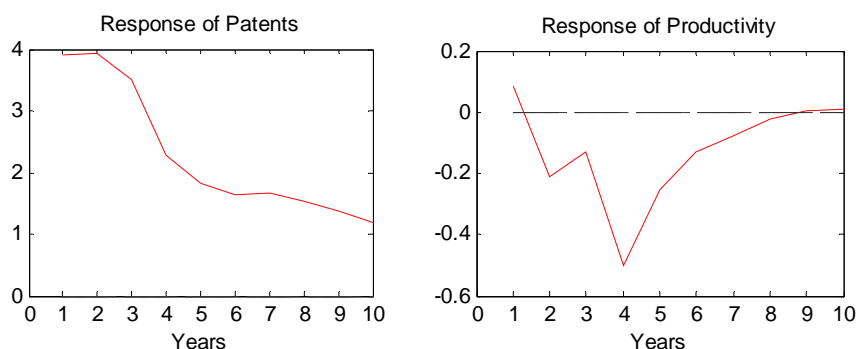


Figure I-9: The stock of patents



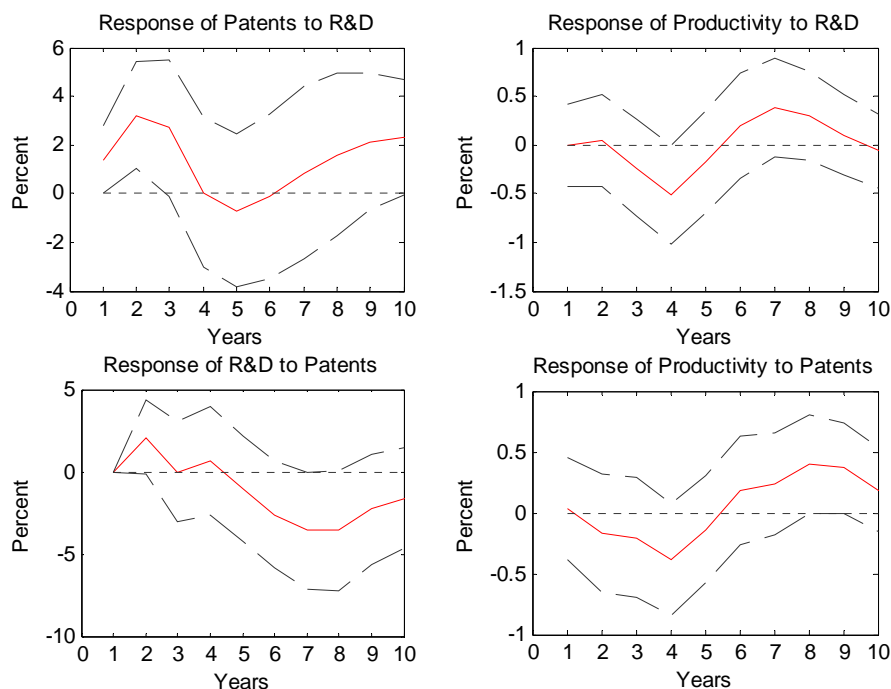
Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line. The responses are from a VAR with the stock of patents and productivity. A time trend with break in trend in 1973, a change in intercept in 1930, and dummies for The Great Depression and WWII are included in the estimation. $p = 6$ lags are used as suggested by the AIC. However, the response functions are robust to using five lags.

Figure I-10: Shock to the stock of patents, 1889-2002



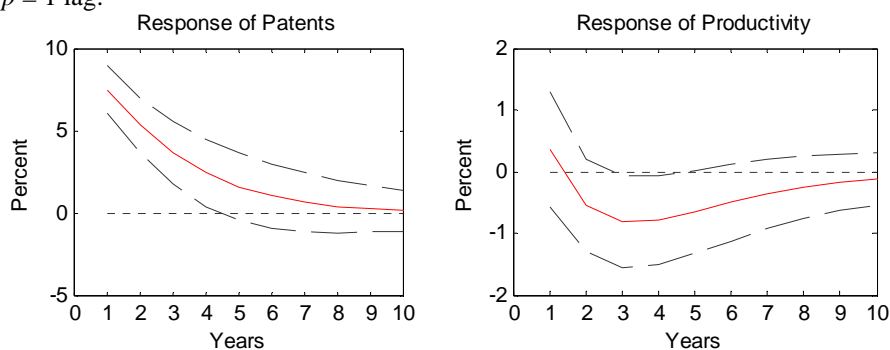
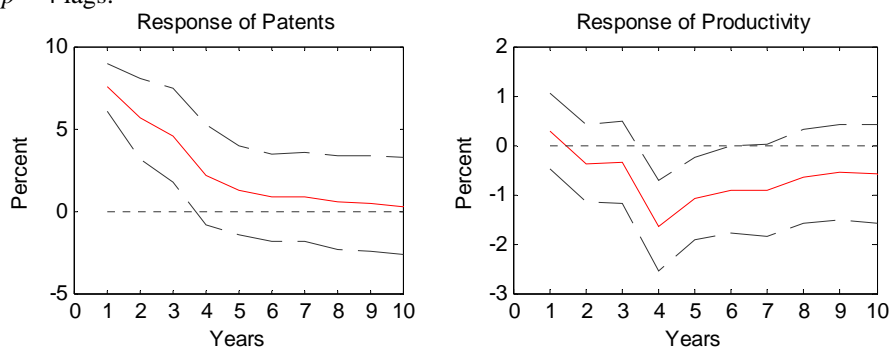
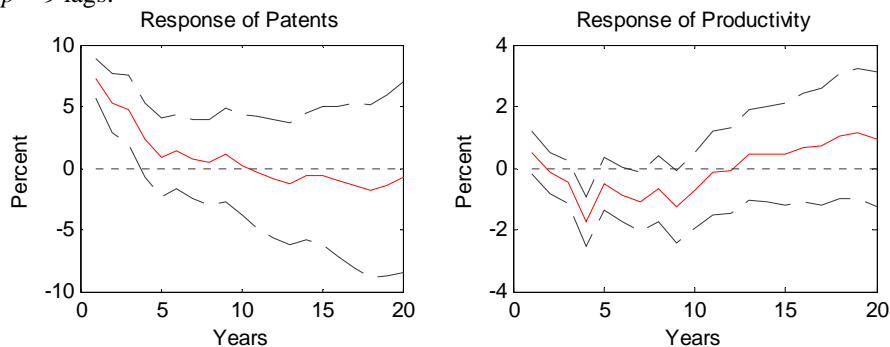
Note: The solid line signifies the impulse response function to a one unit shock to the orthogonal error term in the patent equation. The horizontal dashed line indicates the zero-line. A time trend with break in trend in 1973, a change in intercept in 1930, and dummies for The Great Depression and WWII are included in the estimation. 4 lags are used. The responses indicate the numerical responses of the logarithm of the given variable. The size of the shock is different than in the previous figures since the normalization in the system is different.

Figure I-11: Responses to a patent shock in a restricted model, 1889-2002



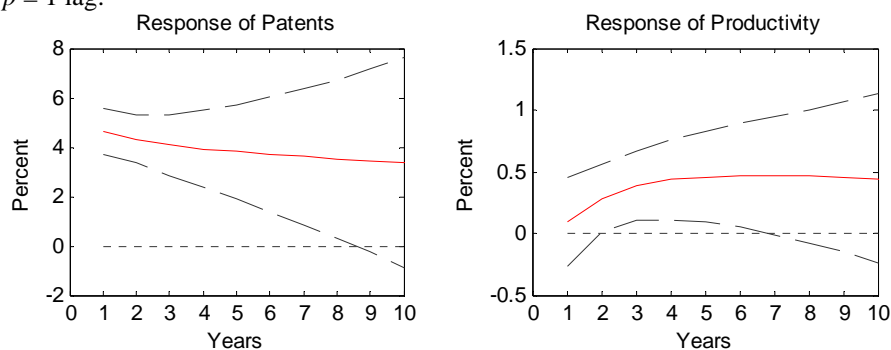
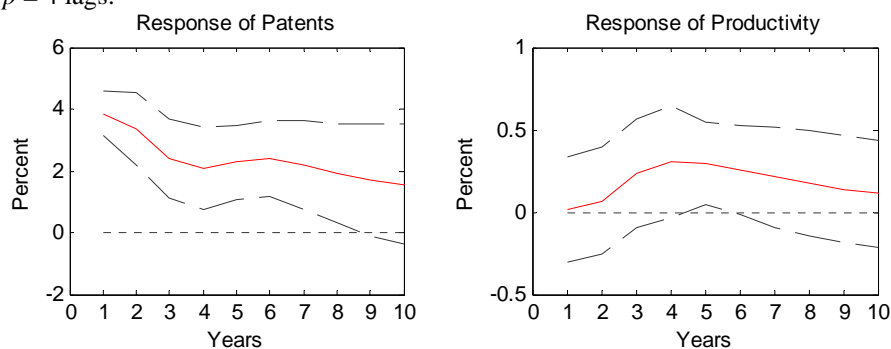
Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line. The responses are from a VAR with R&D, patents, and productivity. The time period covers 1935-1997. A time trend with break in trend in 1973 is included in the estimation. $p = 4$ lags are used as suggested by the AIC. The right hand column depicts responses of productivity to either an R&D shock or a patent shock. The left hand column depicts responses of patents and R&D to a shock to R&D and patents, respectively.

Figure I-12: Response of productivity to an R&D and a patent shock, 1935-1997

Panel A. 1889-1940 $p = 1$ lag: $p = 4$ lags: $p = 9$ lags:

Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line. The responses are from a VAR with patents and productivity over the time period 1889-1940. The first row employs $p = 1$ lag in the estimation, whereas the second row uses 4 lags. The third row employs $p = 9$ lags. A time trend with a change in the intercept in 1930 is included in the estimation. If a dummy for The Great Depression is included, the overall response is unchanged. However, it is then only significant when using 4 and 9 lags. I choose to leave out this dummy in order to keep the maximum degrees of freedom.

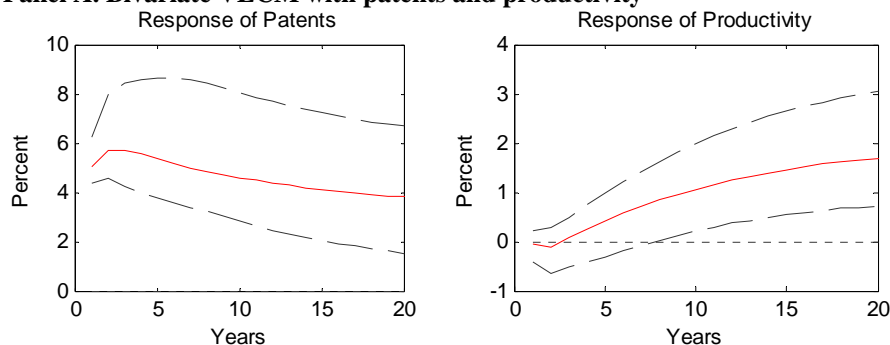
Figure I-13: Two sample periods, continued on next page

Panel B. 1948-2002 $p = 1$ lag: $p = 4$ lags:

Note: The solid line signifies the impulse response function. The thick dashed lines indicate 2 standard error bands estimated by Monte Carlo. The horizontal dashed line indicates the zero-line. The responses are from a VAR with patents and productivity over the time period 1948-2002. The first row employs $p = 1$ lag in the estimation whereas the second row uses 4 lags. A time trend with a break in trend in 1973 is included in the estimation.

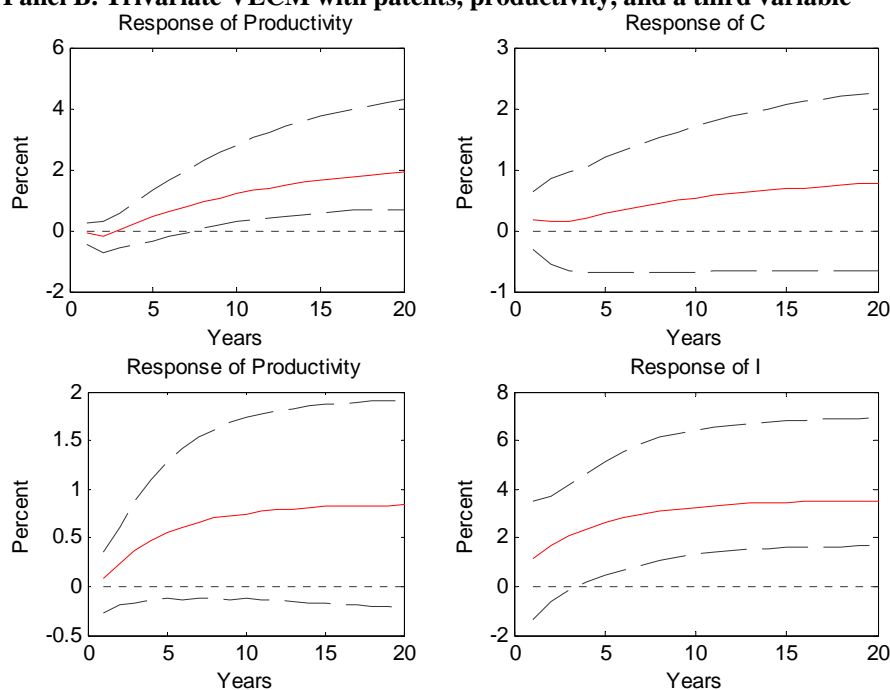
Figure I-13 (continued): Two sample periods

Panel A. Bivariate VECM with patents and productivity



Note: The solid line signifies the impulse response function. The thick dashed lines indicate 95 percent confidence intervals estimated by Hall bootstrapping methods with 10,000 draws. The horizontal dashed line indicates the zero-line. The responses are from a VECM with patents and productivity over the time period 1948-2002. 1 lag in differences is included to be consistent with the following responses. However, using 0 lags in differences as suggested by the AIC does not change the responses, although the productivity response does not become statistically significant until a few years later when using 0 lags in differences.

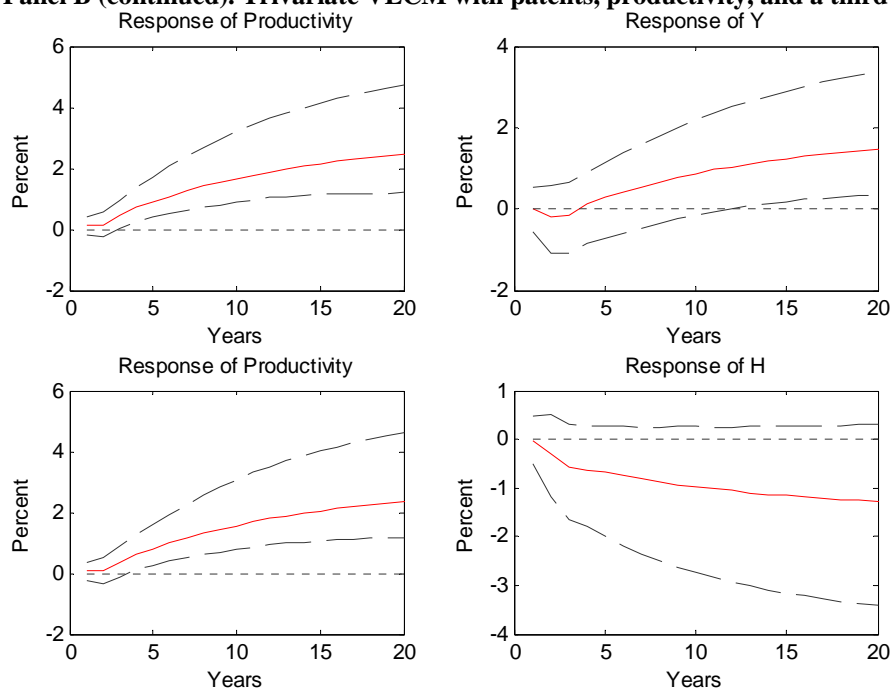
Panel B. Trivariate VECM with patents, productivity, and a third variable



Note: The solid line signifies the impulse response function. The thick dashed lines indicate 95 percent confidence intervals estimated by Hall bootstrapping methods with 5,000 draws. The horizontal dashed line indicates the zero-line. The responses are from a VECM with patents, productivity, and a third variable, depending on the measure of interest. The time period is 1948-2002. For consumption, C, 1 lag in differences is used as suggested by the AIC. For investment, I, 0 lags in differences are used as suggested by the AIC.

Figure I-14: Responses from a post-WWII VECM, 1948-2002, continued on next page

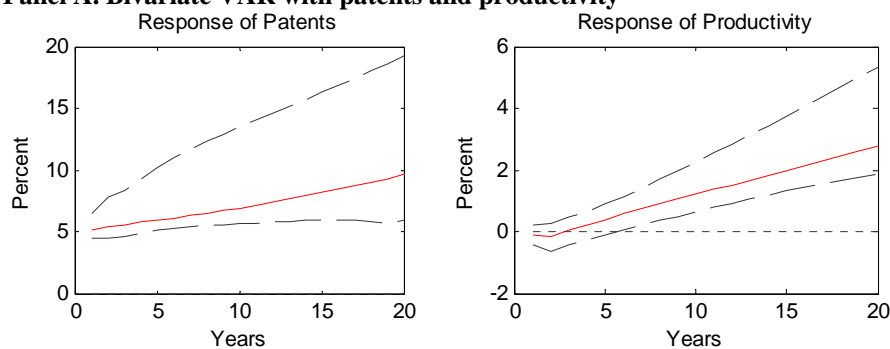
Panel B (continued). Trivariate VECM with patents, productivity, and a third variable



Note: The solid line signifies the impulse response function. The thick dashed lines indicate 95 percent confidence intervals estimated by Hall bootstrapping methods with 5,000 draws. The horizontal dashed line indicates the zero-line. The responses are from a VECM with patents, productivity, and a third variable, depending on the measure of interest. The time period is 1948-2002. For both output, Y, and hours, H, 1 lag in differences is used as suggested by the AIC.

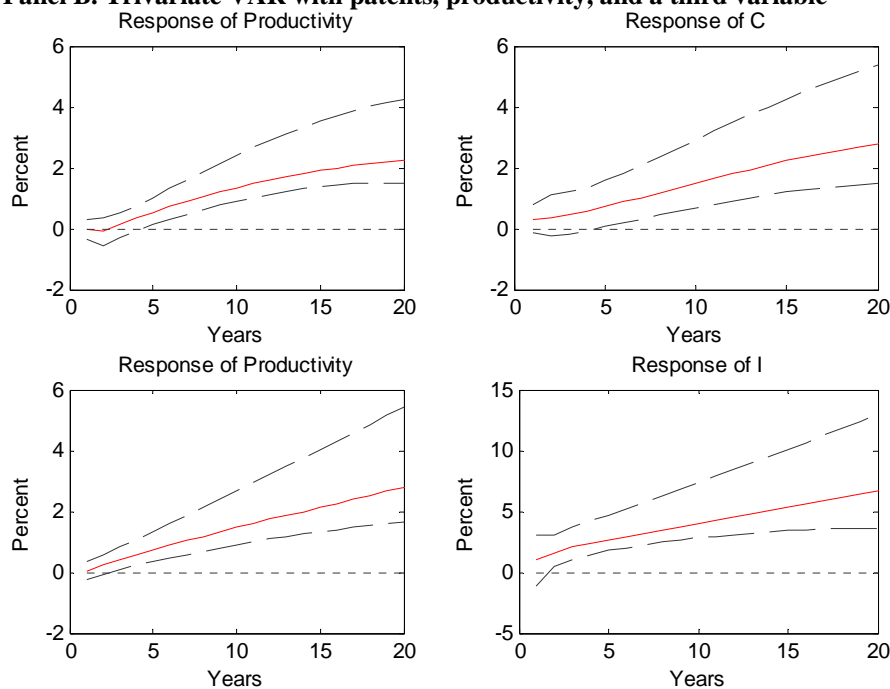
Figure I-14 (continued). Responses from a post-WWII VECM, 1948-2002

Panel A. Bivariate VAR with patents and productivity



Note: The solid line signifies the impulse response function. The thick dashed lines indicate 95 percent confidence intervals estimated by Hall bootstrapping methods with 5,000 draws. The horizontal dashed line indicates the zero-line. The responses are from a VAR with patents and productivity over the time period 1948-2002. No deterministic trend included in the estimation. 2 lags are used to be consistent with the corresponding VECM above. Using 1 lag as suggested by the AIC does not change the responses.

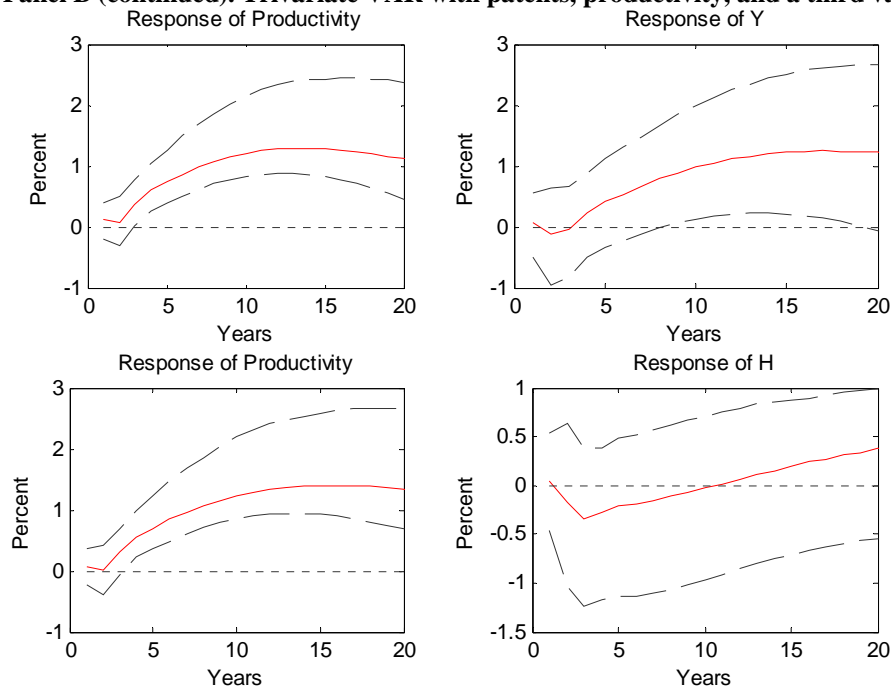
Panel B. Trivariate VAR with patents, productivity, and a third variable



Note: The solid line signifies the impulse response function. The thick dashed lines indicate 95 percent confidence intervals estimated by Hall bootstrapping methods with 5,000 draws. The horizontal dashed line indicates the zero-line. The responses are from a VAR with patents, productivity, and a third variable, depending on the measure of interest. The time period is 1948-2002. No deterministic trend included in the estimation. For consumption, C, 2 lags are used as suggested by the AIC. For investment, I, 1 lag is used as suggested by the AIC.

Figure I-15: Responses from a post-WWII VAR, 1948-2002, continued on next page

Panel B (continued). Trivariate VAR with patents, productivity, and a third variable



Note: The solid line signifies the impulse response function. The thick dashed lines indicate 95 percent confidence intervals estimated by Hall bootstrapping methods with 5,000 draws. The horizontal dashed line indicates the zero-line. The responses are from a VAR with patents, productivity, and a third variable, depending on the measure of interest. The time period is 1948-2002. No deterministic trend included in the estimation. For both output, Y, and hours, H, 2 lags are used as suggested by the AIC.

Figure I-15 (continued). Responses from a post-WWII VAR, 1948-2002

I.J. Data Appendix

Patent data

Patent data are total annual utility patent applications received by the U.S. Patent and Trademark Office for the period 1889 – 2002. Patents granted are from the same source.

Labor productivity, hours, and output in private business

Data for labor productivity (Output per Manhour), real output, and hours are from Kendrick (1961) table A-XXII and table A-X for the period 1889 – 1946 and from the Bureau of Labor Statistics (BLS) for the period 1947-2002. The series are spliced by multiplying the pre-1947 data by the ratio of the BLS data in 1947 to the Kendrick data in 1947.

Real GDP, Consumption, Investment

Real GNP is from Balke and Gordon (1989) for the period 1889-1928. Real consumption expenditures and gross private investment are from Kendrick (1961), Table A-IIa for the period 1889-1928. Nominal consumption and GNP are from Kendrick (1961), Table A-IIb for the period 1889-1928. For the period 1929-2002, nominal GDP, chain-weighted GDP, consumption, and investment are from Bureau of Economic Analysis (BEA), NIPA data. The series were spliced in 1929 by multiplying pre-1929 data with the ratio of the NIPA data in 1929 to Kendrick's data in 1929.

Income and Wage inequality

The top decile and other fractiles for the income share, 1917-1998, and the top decile and other fractiles for the wage share, 1927-1998, are from Piketty and Saez (2003).

R&D

R&D for 1935-1997 is investment in privately financed research and development, deflated by chain-type price index for GDP and as computed by NPA Data Services. The data are available in Terleckyj, Levy, and Coleman (1997).

Diffusion of products

Data on spread of products into American households, 1900-2004, are provided by W. Michael Cox, Federal Reserve Bank of Dallas.

Data on diffusion of electric power are from Du Boff (1979).

Stock price index

Data on stock prices are real S&P Composite Stock Price Index 1889-2002. Data are available at a monthly frequency on <http://www.econ.yale.edu/~shiller/data.htm>. This site contains updated data for chapter 26 of Market Volatility, Shiller (1989), and Irrational Exuberance, Shiller (2005). The January annualized values are the values used by Shiller in Market Volatility, chapter 26 and updated by Shiller while the June values are taken directly from the monthly data as computed by Shiller.

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Chapter II

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

Abstract

This paper 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 paper 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.

I thank Bryan D. Goudie for co-authoring this chapter and Valerie Ramey and Yixiao Sun for helpful comments and suggestions.

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 paper examines the effects of increased military spending on the development of new technology. The result will have important consequences for modeling the evolution of the 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 paper puts focus 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 GDP, and by the time of the peak¹ 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 percent². As a result of this large exogenous change in military spending, the large defense contractors faced considerable increases in prime contract awards that were unrelated to aggregate productivity.

Although the buildup was exogenous to aggregate U.S. economic fluctuations, it may be that the individual awards are assigned at the firm level based on the economic performance of the firms. 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, military prime contract awards in the period of a big exogenous military buildup can therefore be considered exogenous to the economic conditions at the firm. The paper discusses this issue and provides evidence that only few of the contracts awarded to the big defense contractors are competitively procured.

Motivated by a macroeconomic question, this paper examines the effects of military spending on the development of new technology and productivity at a microeconomic level. Specifically, the paper explores whether military prime contract

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.

(MPC) awards result in significant changes in research and development (R&D) and patenting and take into account dynamics across time through use of panel vector autoregressions (VARs). The paper uses U.S. military prime contract (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 time period from 1969 to 1993 which includes the large military buildup in the 1980s. With this data set the paper 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 us to comment on how military demand shocks can affect the neoclassical model.

The analysis employs a data set of firm-level Department of Defense contracts that have been created based on the Department of Defense publications that list the top 100 military prime contractors and completed with aggregation of the underlying source data of the individual contracts. The paper can then provide a thorough statistical analysis of the effects of military prime contracts on the development of new technology and on productivity. Following a positive MPC shock, we conclude that labor productivity, which is computed as average revenue product, in a bivariate system increases after immediate positive responses of both sales and employment. Privately expensed R&D increases a few years after the shock, indicating that military contracts 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.

The paper 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 presents some of the existing literature on the subject and outlines how military demand can affect 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 which 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 (2006) shows how the initial anticipation effect of government spending can have dramatic consequences for the estimated effects of a government spending shock. However, the anticipation effect of government spending is mainly important when using quarterly data. Specifically, Ramey finds that different identification methods provide similar results when applied to annual data. As such, our study does not suffer from problems with 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 and 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 paper can add significantly to the existing micro- and macroeconomic literature. With the firm-level data set, this study can provide micro evidence for the resulting macroeconomic effects. This paper is therefore important for understanding how macroeconomic effects arise as a result 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 military prime contracts lead to significantly more resources put into R&D, then firm productivity may increase over time as a result 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

$$(1) \quad F_H(K_t, H_t; z_t) = \mu_t w_t.$$

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 1. If capital and technology are taken as given, labor demand cannot shift in the short run as a result 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 paper 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 taking out research and development 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 paper 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. Indeed the new technology can increase the range and quality of goods produced. Furthermore, the increased demand may alone result in learning-by-doing effects which 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

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

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

The purpose of this paper 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 defense expenditures.

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”. These publications list the top 100 military prime contractors that are receiving military prime contract awards in any given fiscal year. Thereby, the analysis includes firms whose main businesses rely on military prime contracts. However, several firms enter and exit the top 100 list over time. To fill out the missing observations this paper aggregated the raw data on MPC awards at the firm level, collected from the Department of Defense Directorate for Information Operations and Reports website. These data contain a complete list of all individual contracts awarded during the sample period.

The raw data reveal that the number of contracts received by any one firm varies considerably among companies. In addition, a large military company with subsidiaries

receives 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 Christiansen and Goudie (2007) (chapter III of this dissertation) contain a thorough description of this underlying data set, although their 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 military contracts does not grow with the rate of inflation as measured by the GDP deflator. As an alternative price deflator this study therefore used a price index for national defense consumption expenditures and gross investment. However, this series is only available starting in 1972. As such, using this series limits the time series 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 military prime contract 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, as mentioned above, Ramey (2006) find that the initial anticipation effect is not very important in annual data. Furthermore, this paper has tried including stock prices in all the computations below. This should account for any expectations formed prior to receiving the military contract. Including stock prices in the analysis did not change the conclusions, indicating that the timing of the contract awards is not important in explaining the results.

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. Before 1977, that fiscal year was defined as July through June.

Data on total sales, employment, stock prices, and research and development (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 big 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 big defense contractors such as Boeing, Grumman, Lockheed, McDonnell Douglas, Northrop, and Raytheon. The full list of firms in the sample can be found in table II-1.

The aggregate real military prime contract value for the selected companies is depicted across time in figure II-1 together with total aggregate real U.S. military prime contract 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. military contracts. 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 paper uses the average revenue product as a proxy for labor productivity data. The average revenue product, hereafter referred 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 paper 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 expenses are deflated with the GDP deflator. It is important to note that R&D expenses account for company expensed R&D. Federally funded R&D is therefore not included in this variable. For a few companies, government financed 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 (2007) (chapter I of this dissertation). 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 till the date of grant, the last few years of the dataset contain a decrease in the patent application count as a result of data truncation. Patents granted in 2000 or later but which had an application date in 1999 or earlier are as such not counted in the sample. Because the sample period used in this paper ends in 1993, this issue should 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 the study with 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 as a result 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 paper 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 time 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 the paper treats the merging firms as one firm over the full sample period. The paper 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 military prime contracts were awarded at the firm level in the period 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 paper. As a result of data limitation, the table is based on data from 1998 to 2003. The paper thereby assumes that the nature of the award method was unchanged between the 1980s military buildup and the military spending in the late 1990s.

The table describes that these firms largely receive military prime contracts that have not been put out for competitive bids, mainly as 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 mainly awarded contracts through full and open competition, but most often with only two bidders. These contracts are mainly fixed price contracts. Overall, the paper finds strong evidence that MPC awards are given to the top military prime contractors primarily without strong competitive pressure. As a result, the analysis concludes that MPC awards can be assumed exogenous to firm-level productivity.

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 paper estimates an unbalanced panel vector autoregression (PVAR) with p lags and m variables. The basic unbalanced PVAR looks as follows:

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

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

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

w_{nt} is an $m \times 1$ vector of variables for firm 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 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

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:

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

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

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

The paper estimates this system by OLS where the individual effects are estimated. In general, under the assumption of a fixed T and $N \rightarrow \infty$, 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 time periods, T is assumed

⁴ Standard errors are estimated by Monte Carlo with 2000 simulations. However, we also estimated (not shown in this version of the paper) 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.

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.

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 military prime contract 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 (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 indeed 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 1 lag. However, since military contracts may last longer than one year, only including one lag may introduce omitted variable bias. This paper therefore experiments with different lag lengths and chooses to include 3 lags in the benchmark analysis.

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.

The impulse response functions from a bivariate model with different variables and 90 percent confidence intervals are illustrated in figures II-2 through II-6, using 45 firms for the estimation, except in the case of R&D where 43 firms are included as a result 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. Figure II-2, panel A, depicts results of including both 2 and 3 lags, while panel B 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, military prime contract 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-3 and II-4), over time leading to an increase in productivity as a result of the relatively stronger response of sales. Although the military prime contract 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 military prime contracts 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-5 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 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 of military prime contracts being 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 military prime contract 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 Money⁷ 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 also during the Iraqi war outperformed the market is consistent with the fact that stock prices increase over several years also in this paper's analysis.

In a bivariate PVAR with R&D and MPC (figure II-6), 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.

⁷ CNN Money.com, November 10, 2005.

However, this response does become significant at the long horizon for some choices of lag lengths (not shown). This gives an indication that military contracts 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 privately expensed 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 happen immediately but that allowing for time dynamics as done in this paper 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-7, II-8, and II-9 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-7, clearly showing how more resources are put into research and development when prime contracts are awarded. Furthermore, any positive effects on MPC awards of labor productivity shocks are not present in the trivariate analysis. This provides further evidence that contracts are not awarded to the firm with highest productivity. Interestingly, an MPC shock in the trivariate system in figure II-7 only leads to insignificant effects on productivity.

Figure II-8 shows 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-9 reports results from a PVAR with SP, LP, and MPC, using two and three 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 the paper chooses to order SP first in the trivariate system, the result is robust to ordering SP last.

This section has shown that stock prices, research and development, and in most cases also productivity increase significantly following a military prime contract award. Furthermore, the analysis supports the assumption that military contracts 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 then became possible for universities and small businesses to retain title to inventions that were funded under federal research and development 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 big 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 in 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 as a result of this policy change. To take this issue into account, this paper 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 companies⁸ 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.

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 the paper.

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 paper. 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 paper therefore analyzes this scenario. Of the companies in the sample that are included in the NBER patent database and have information to enable a match 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 figure II-10. 2 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-10 illustrates how the rate of patenting increases insignificantly after an initial insignificant decrease. However, when considering the 1984-1993 period in figure II-10, 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-10, 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-10 there is some evidence that a patent shock results in military prime contract 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 privately expensed 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.

As explained above, 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-11. The results are robust to leaving out the technology firms.

Additionally, figures II-12 and II-13 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, the paper 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 (2007) (chapter I of this dissertation).

Figure II-14 depicts the results from 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 from the bivariate analyses with R&D and patents, respectively. That is, a military prime contract award leads to the development of new technology. In figure II-14 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 research and development 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 businesses are in the oil industry. These companies may be largely 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 paper 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 big 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 field of technology and communication. The analysis also tried excluding these firms from the analysis. Leaving out seven technology companies⁹ 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 paper also tried only including the companies that are traditionally labeled as large defense conglomerates. This excludes companies with main focus on subjects such as oil, technology, communication, and electricity. The impulse response functions from a bivariate PVAR including only defense conglomerates in the sample¹⁰ 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 military prime contracts, indicating that firm productivity is

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

¹⁰ This reduces the sample size to 22 companies.

not the determining factor when military prime contracts 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. Also 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, the paper 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.

It has been argued in this analysis that contract awards are not allocated at the firm level based on the economic performance of the firm. However, 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 paper may contain unresolved endogeneity. The analysis so far suggests that this issue is not the main driving factor behind the results but examination of this concern is a subject for future research.

II.H. Conclusion

This paper 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

paper found evidence that firm productivity increases over time in response to a military prime contract award. This happens as a result of positive responses of both sales and employment with sales showing the strongest response.

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

Overall, the paper concludes that military spending leads to the development of new technology. Thereby, positive effects on productivity can arise also at the aggregate level at the long horizon. 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 Bryan D. Goudie for co-authoring this chapter. The dissertation author is a primary author of this chapter.

II.I. Tables and figures

Table II-1: Companies included in the full sample, continued on next page

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

Table II-1 (continued): Companies included in the full sample

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, continued on next pages**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". <http://www.publicintegrity.org/pns/>

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

Center for Public Integrity states that: “**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”. <http://www.publicintegrity.org/pns/>

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. "Outsourcing the Pentagon". <http://www.publicintegrity.org/pns/>

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	

Center for Public Integrity states that: "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. "Outsourcing the Pentagon"
<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, continued on next page

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.

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.

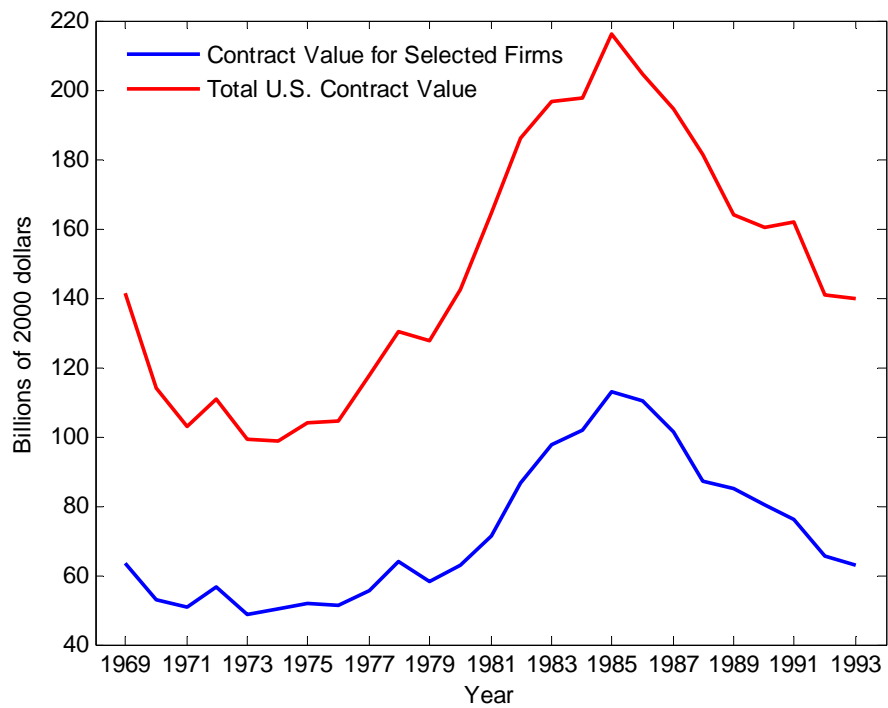
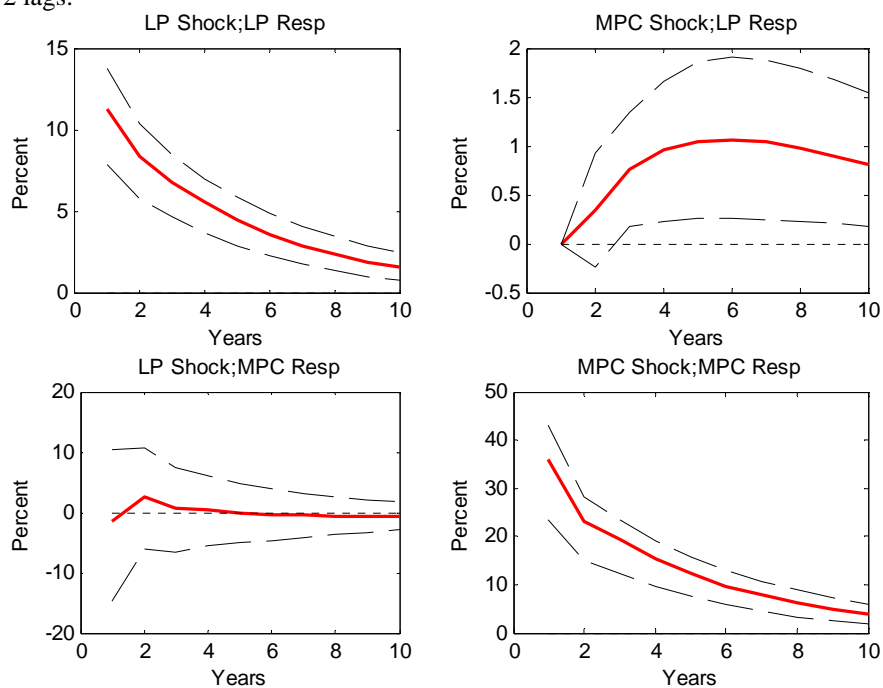


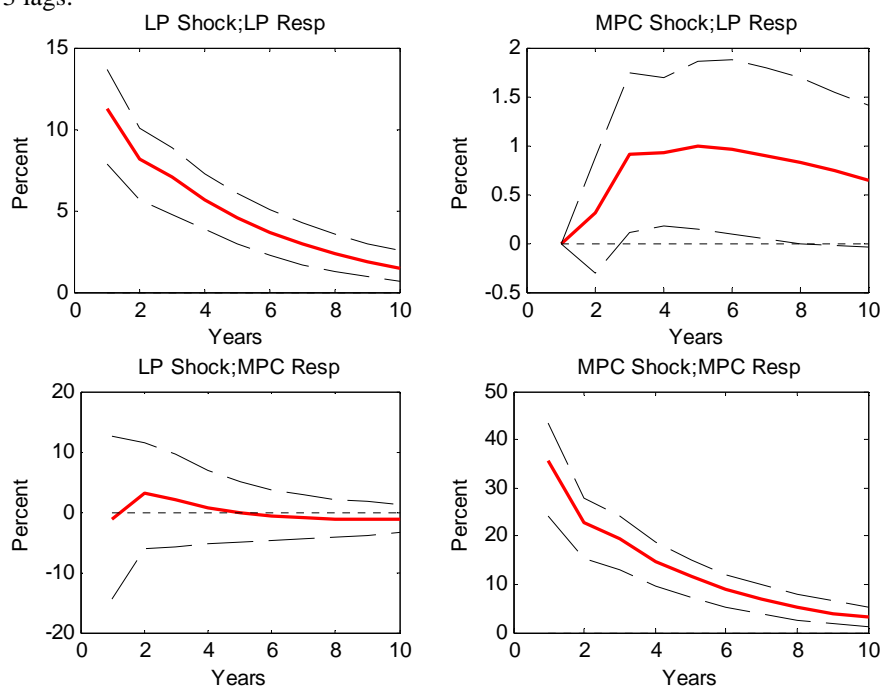
Figure II-1: Aggregate military prime contract awards

Panel A. LP and MPC

2 lags:



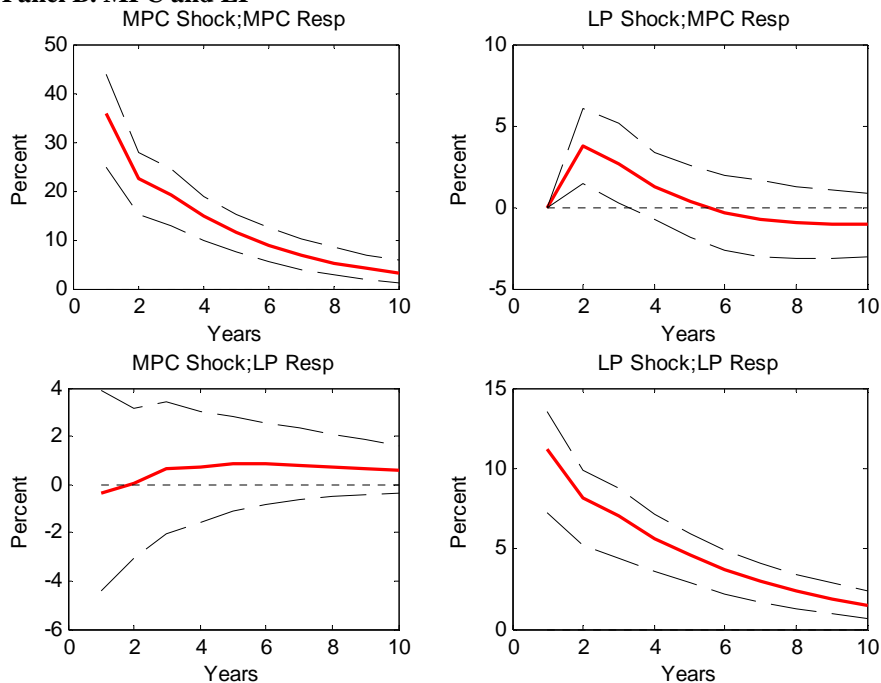
3 lags:



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

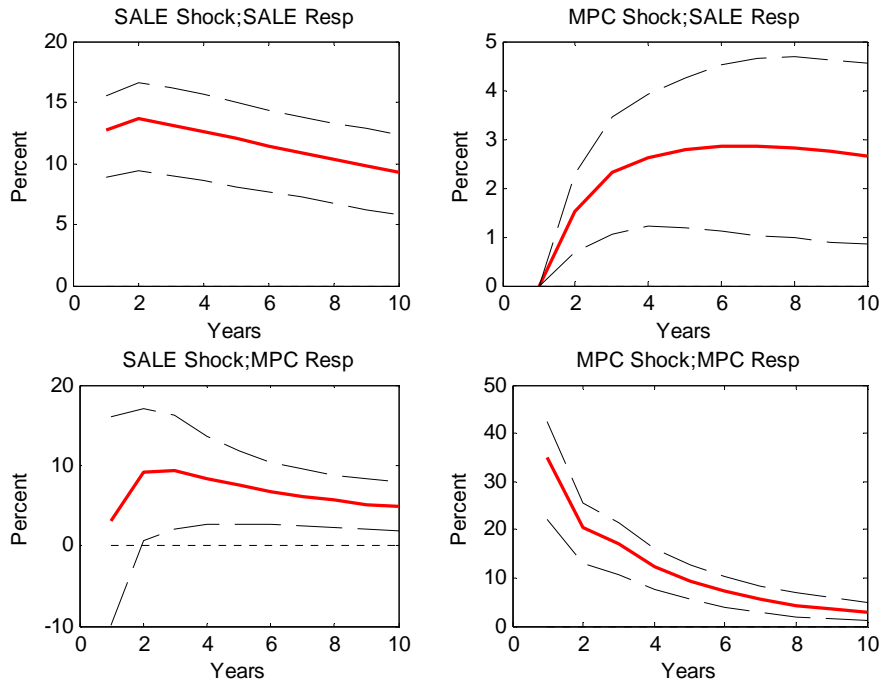
Figure II-2: Bivariate PVAR with LP and MPC, both orderings, continued on next page

Panel B. MPC and LP



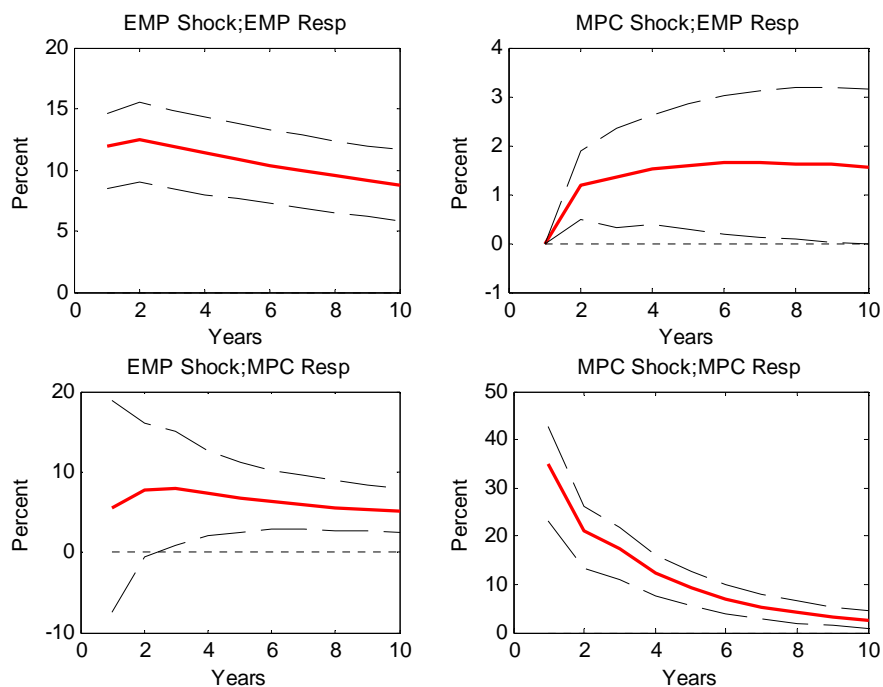
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 45 firms are included, and 3 lags are included.

Figure II-2 (continued): Bivariate PVAR with LP and MPC, both orderings



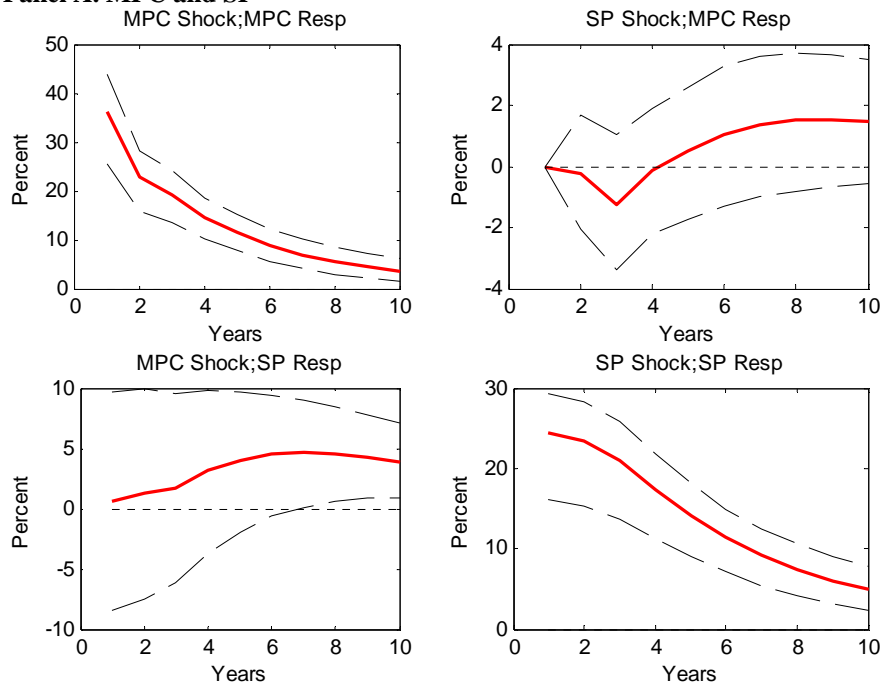
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 3 lags are included.

Figure II-3: Bivariate PVAR with SALE and MPC

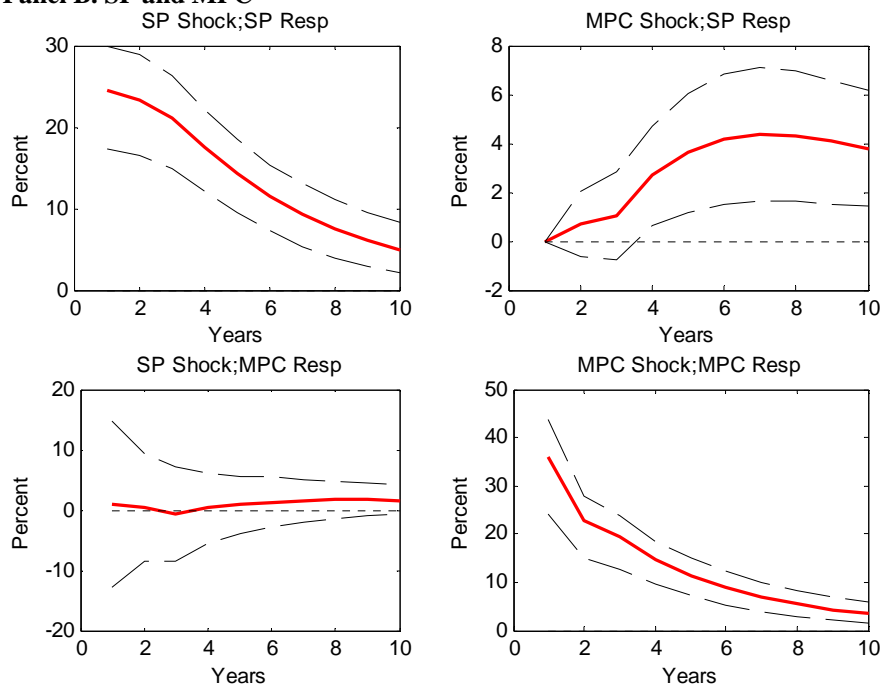


Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 3 lags are included.

Figure II-4: Bivariate PVAR with EMP and MPC

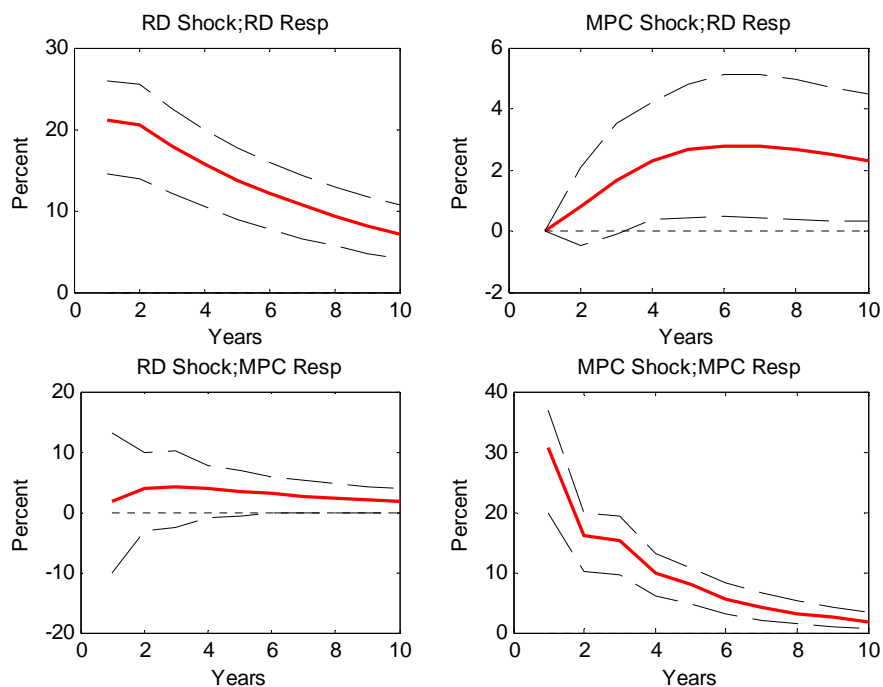
Panel A. MPC and SP

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

Panel B. SP and MPC

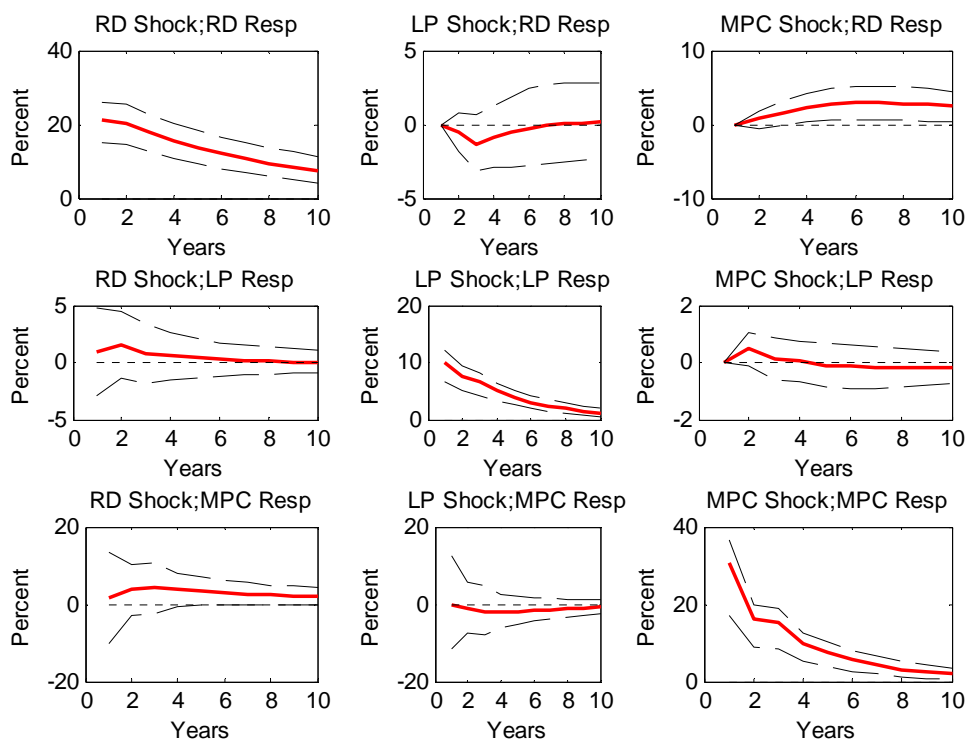
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 3 lags are included.

Figure II-5: Bivariate PVAR with SP and MPC, both orderings



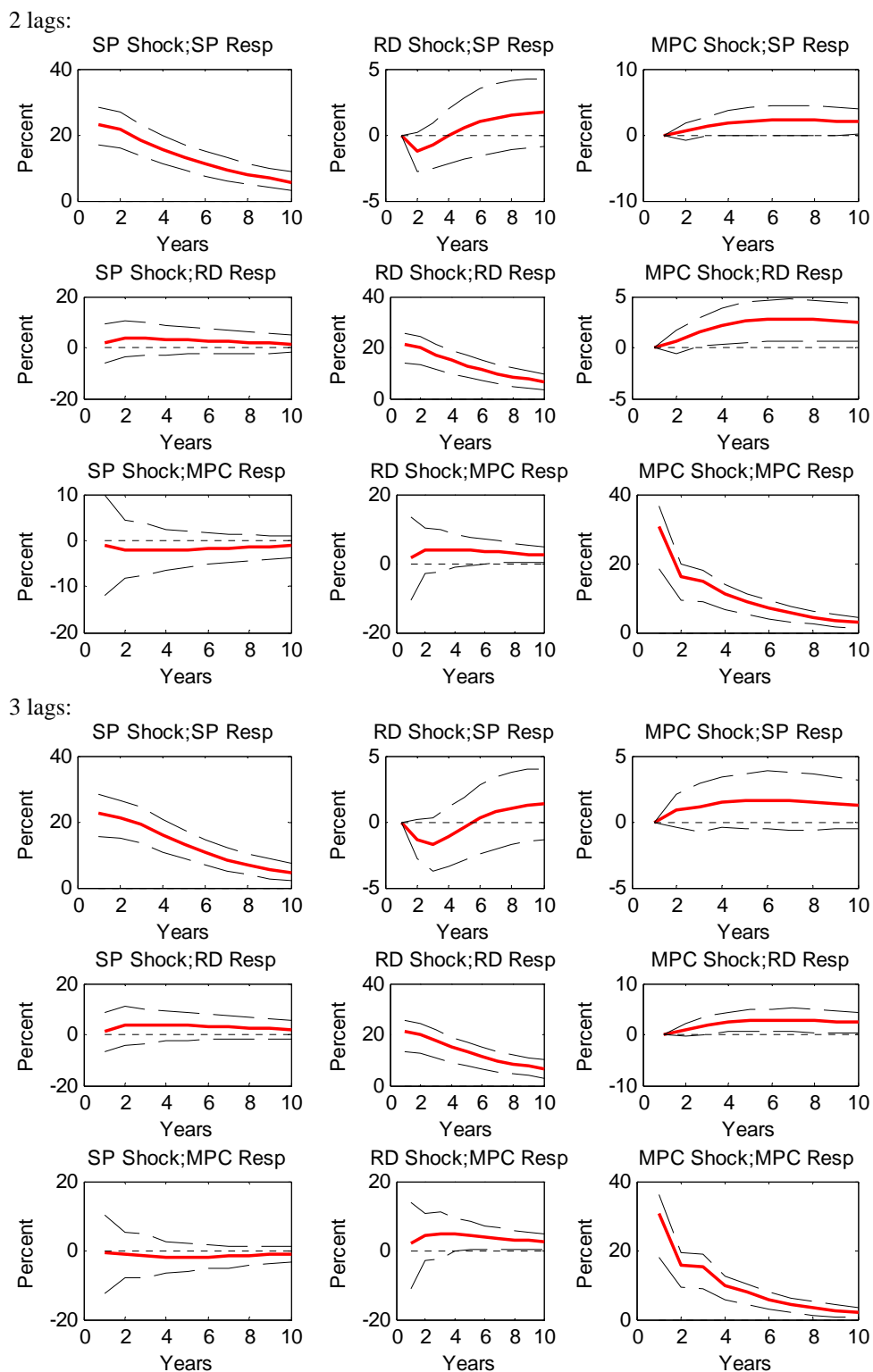
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 43 firms are included. 3 lags are included.

Figure II-6: 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.

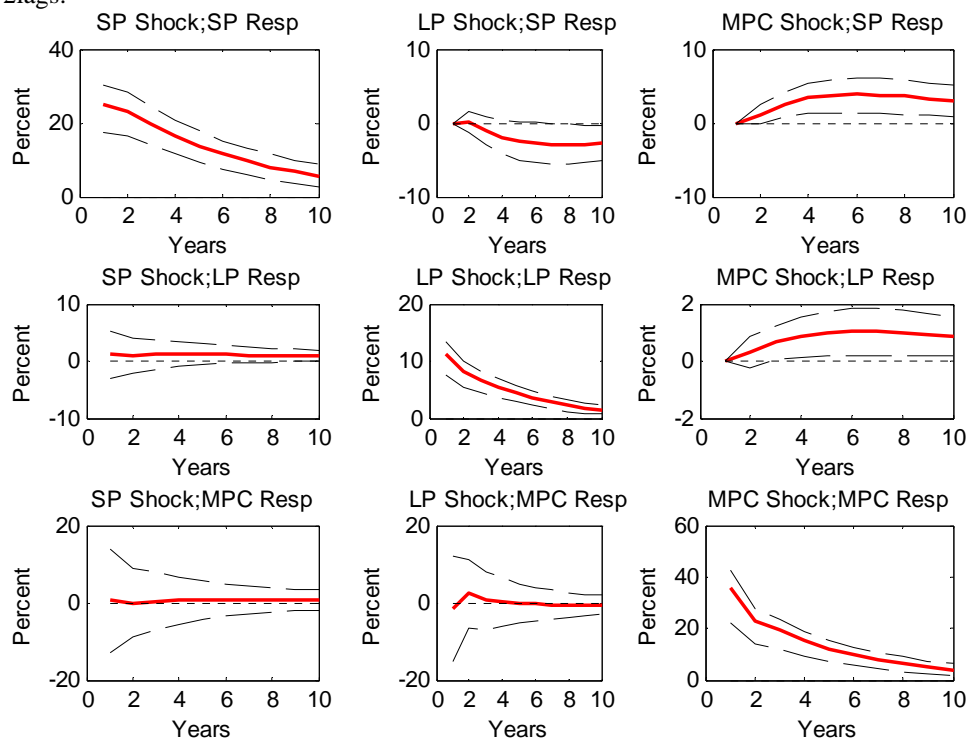
Figure II-7: Trivariate PVAR with RD, LP, and MPC



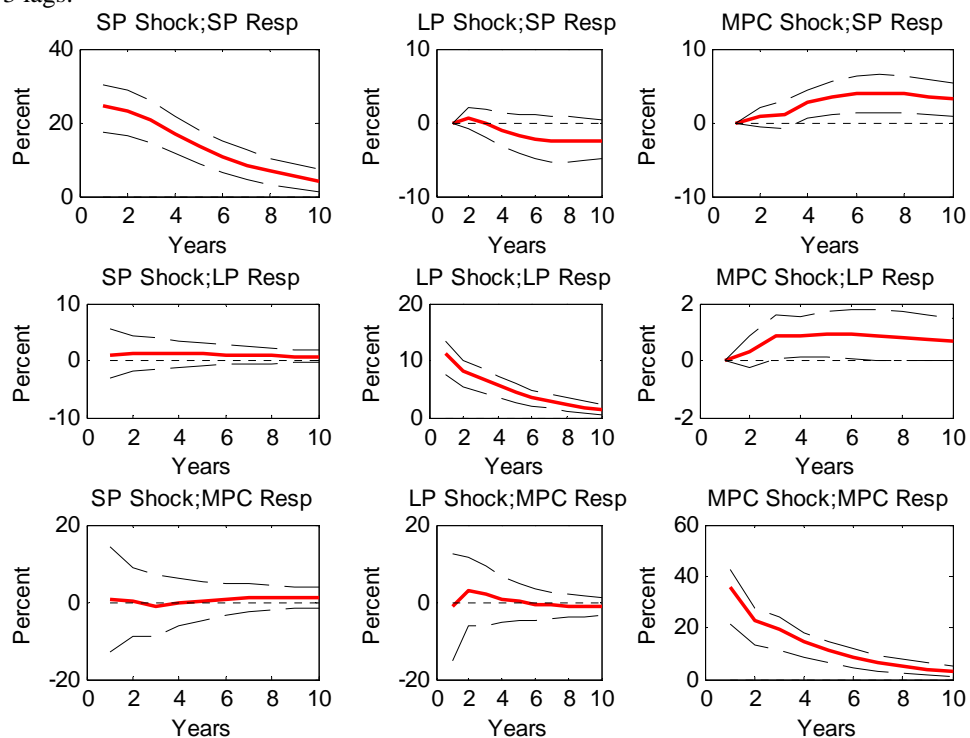
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals.

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

2lags:

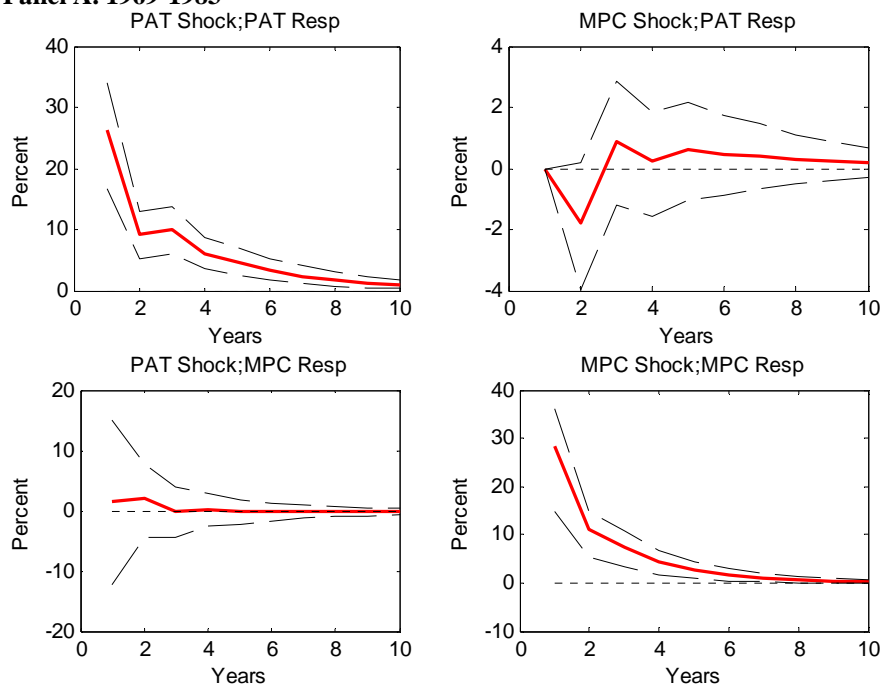


3 lags:

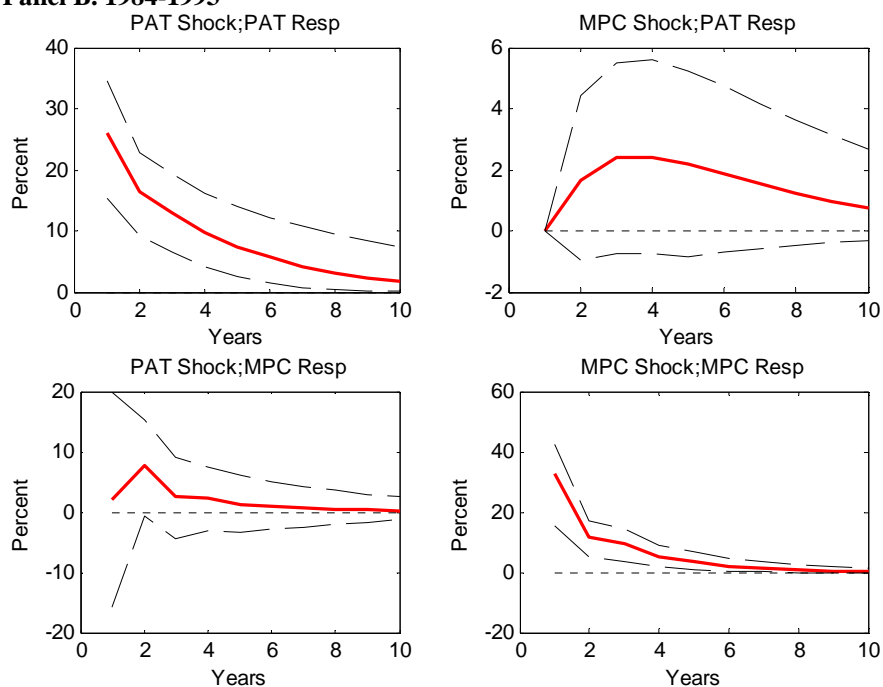


Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals.

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

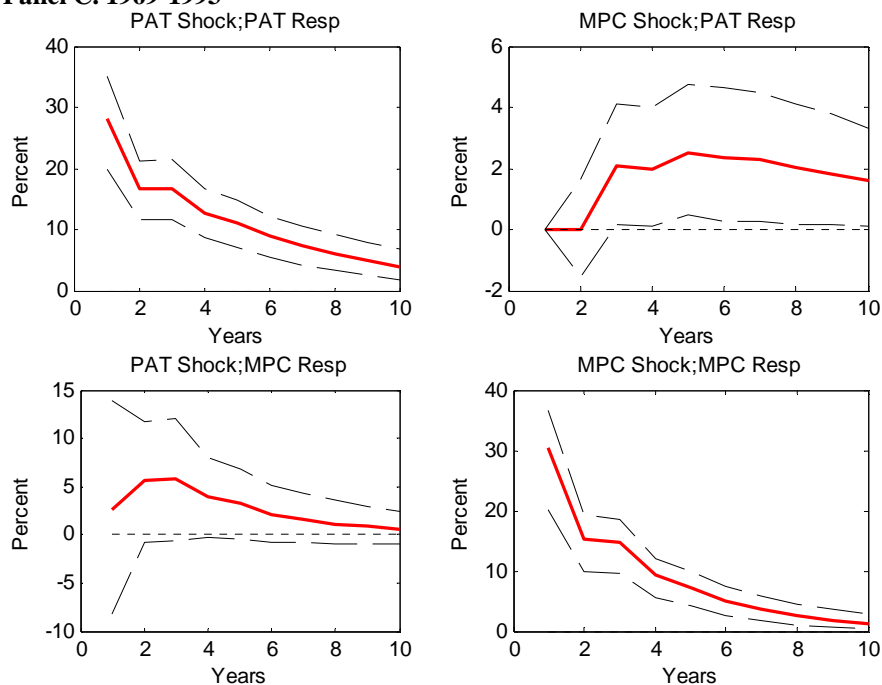
Panel A. 1969-1983

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

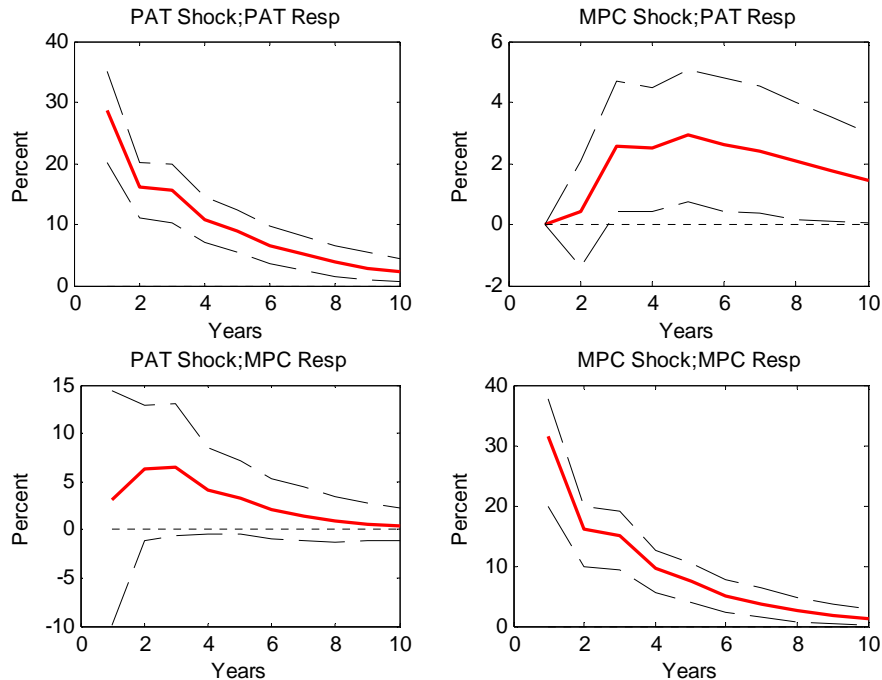
Panel B. 1984-1993

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

Figure II-10: Bivariate PVAR with PAT and MPC, varying sample period, continued on next page

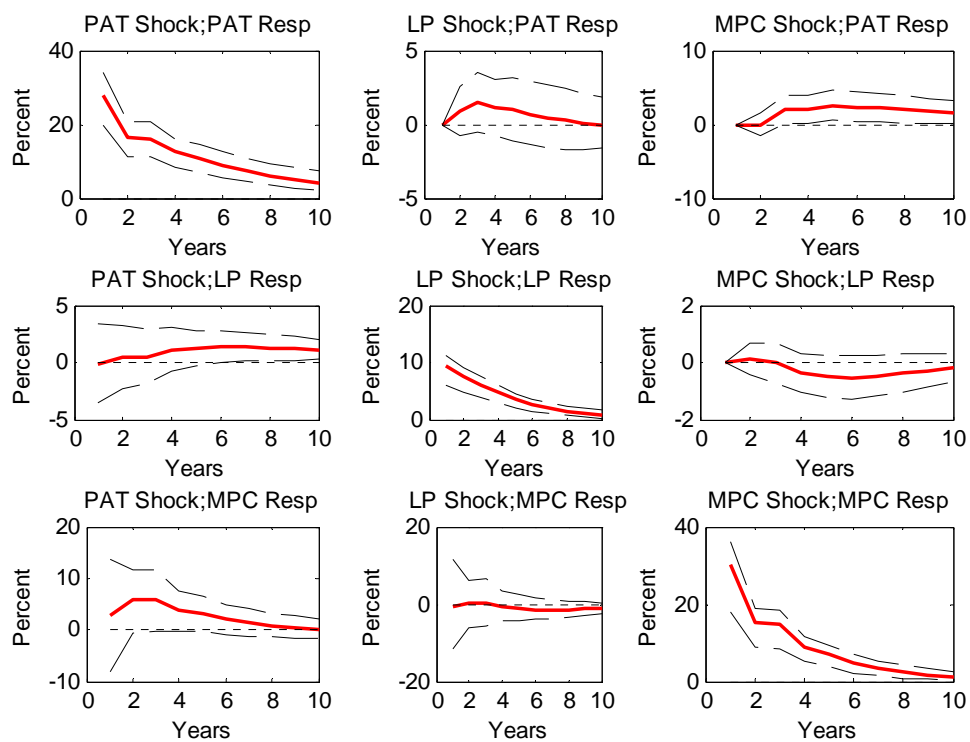
Panel C. 1969-1993

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-10 (continued): Bivariate PVAR with PAT and MPC, varying sample period

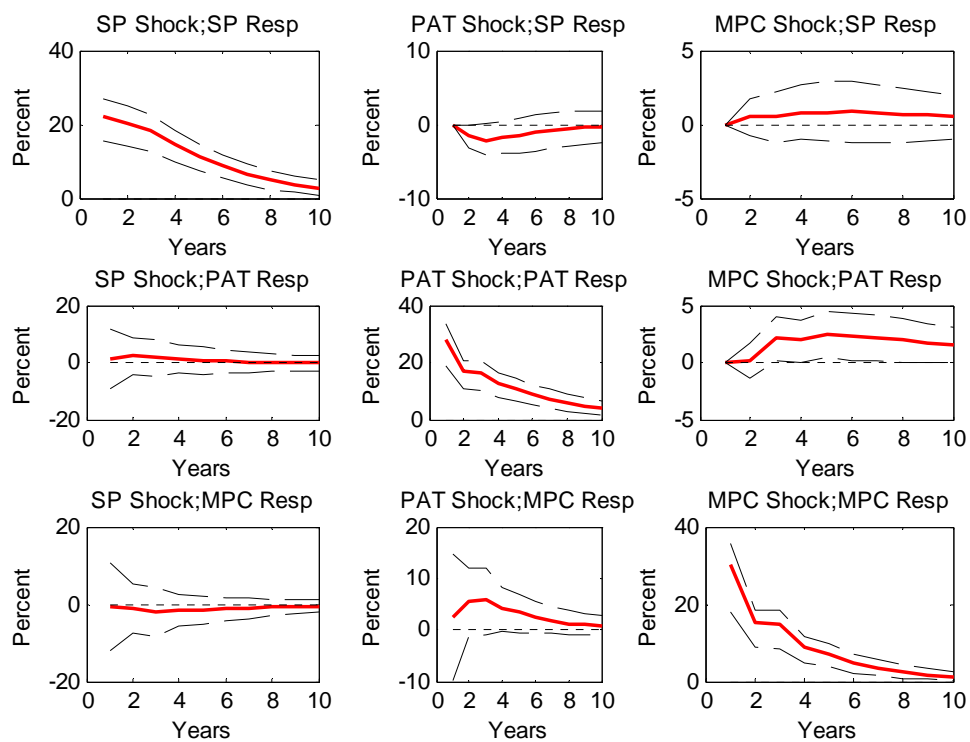
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 34 firms included. 3 lags are included. Technology firms not included in the sample.

Figure II-11: Bivariate PVAR with PAT and MPC, 1969-1993. Excluding tech. 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.

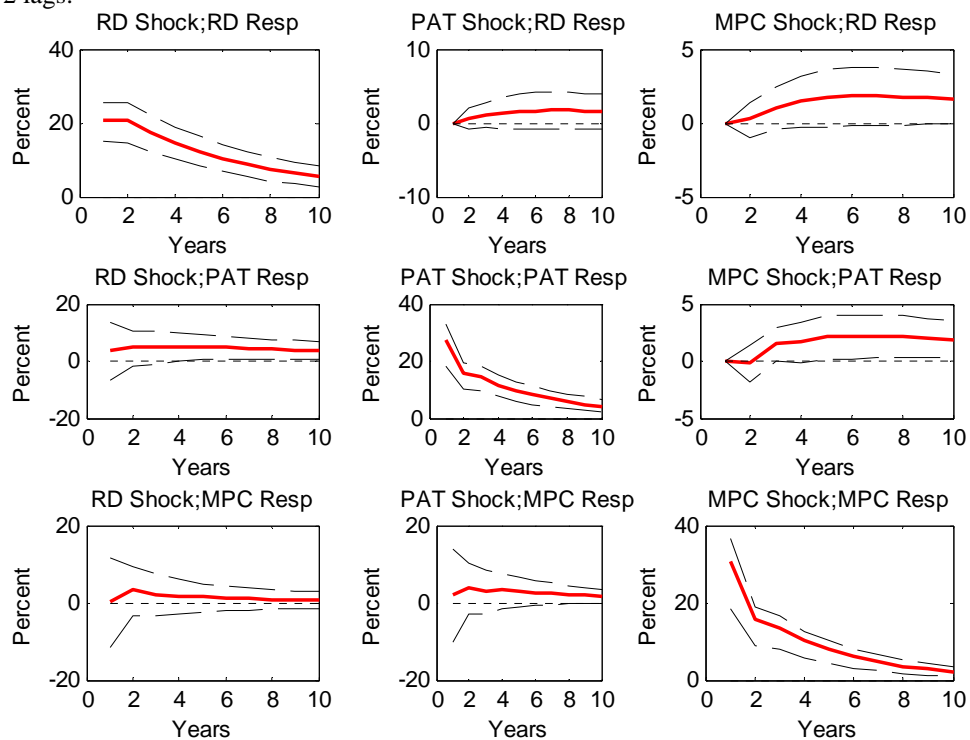
Figure II-12: Trivariate PVAR with PAT, LP, and MPC, 1969-1993



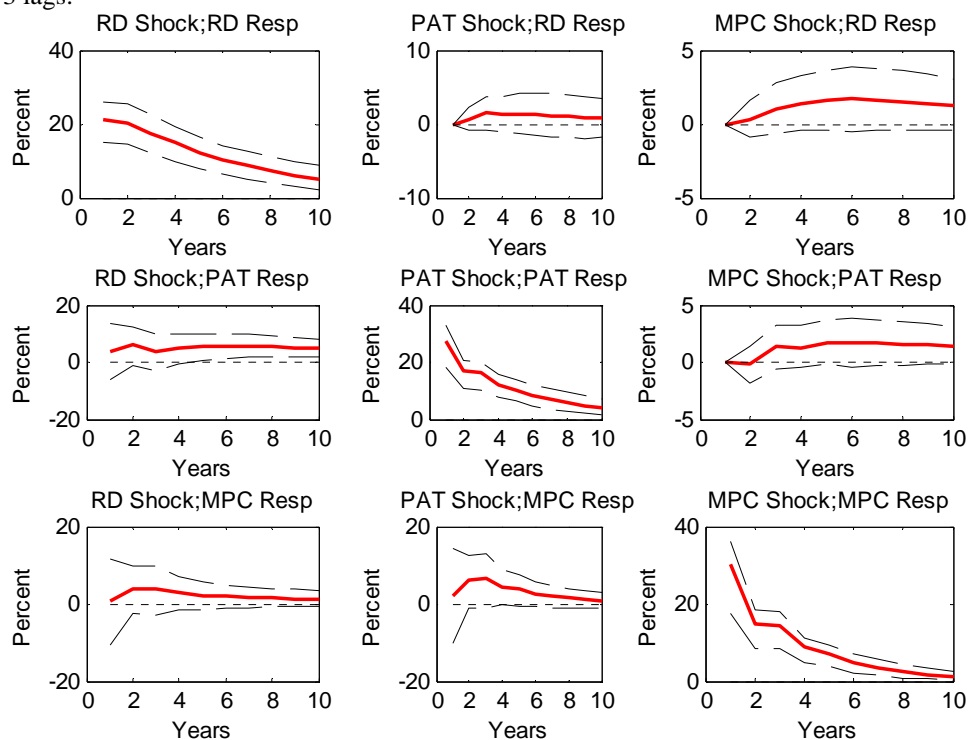
Note: The solid line indicates the impulse response function. The dashed lines are 90% confidence intervals. 3 lags are included.

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

2 lags:



3 lags:



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

Figure II-14: 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 affect regional productivity? Data on Gross Domestic Product by state from the regional economic accounts are used to answer this question. In addition, data on the number of utility patents, sorted by application date, in each state in the U.S. are employed in order to assess whether military spending contributes to technological change. Through panel vector autoregressions with the 50 states and the District of Columbia, the paper 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.

I thank Bryan D. Goudie for co-authoring this chapter.

III.A. Introduction

During the post-WWII period, military spending has experienced large 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. Furthermore, the demand for defense products is not evenly distributed across the United States, and aggregate economic findings occur as a result of variations at the regional level. In 1986 during the Carter-Reagan military buildup, California received \$27.7 billion in military prime contracts, while Idaho received merely \$62.9 million. And even when taking into account population, California continues to outperform most states when considering the dollar amount received as a result of military prime contracting. These spatial differences are important to take into consideration when exploring the effects of military spending.

This paper examines the economic consequences of military prime contracts for labor productivity and the development of new technology at the regional level. Data on Gross Domestic Product by State¹, starting in 1963, have recently become available from the Bureau of Economic Analysis Regional Economic Accounts. Together with regional employment data, this enables the paper to compute labor productivity data at the state level. Furthermore, patent data from the NBER patent database can be sorted by the state of the first inventor, making it possible to perform an empirical and statistical analysis of

¹ Gross domestic product by state is formerly known as gross state product. In this paper both names will be used.

the regional effects of military spending and how military prime contracts may lead to the development of new technology.

The time dimension in this paper is limited to focus on the years around and during the Carter-Reagan military buildup. During this period, the paper can employ data on both productivity and patent applications for each of the 50 states and the District of Columbia. The Carter-Reagan military buildup happened as a result of factors unrelated to the economic conditions in the U.S. as it was initiated after the Soviet invasion of Afghanistan in the end of 1979. Ramey and Shapiro (1998) make a careful description of this event.

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

In section III.B which follows, the paper 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 military prime contracts. Section III.G concludes.

III.B. Related literature

At the regional level, 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 military prime contracts 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 movements in employment growth and unemployment rates are being affected by various driving forces. 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 help 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.

As a result of the recent availability of data on gross state product, this paper can examine the effect of military spending on regional output and compute average labor productivity series as gross state product per employed worker. 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 the paper is able to take into account the dynamic interactions between the economic variables across time. See also Christiansen and Goudie (2007) (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 and the validity of patent counts as a measure of innovative activity. They compare the innovation output indicator developed by the U.S. Small Business Administration to patent data from the United States Patent and Trademark Office 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 military prime contract data are from the Department of Defense Directorate for Information Operations and Reports. These data give information about the dollar value of military prime contracts² awarded to businesses 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 F-16 fighter jets. Examples of products include rechargeable batteries, packing equipment, footwear, food services, jet engines, pharmaceutical drugs, and software.³ 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.⁴ It should be mentioned that these

² The military prime contract data are Department of Defense 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.

³ 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.

⁴ 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 canceled contract for the firm Kiewit Morrison Fischbach. However, the positive corresponding value does not enter in these years which indicates a misreporting in the data. This paper 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.

data do not take into account subcontracting outside the principal place of performance. Therefore, military prime contract data at the state level as used in this paper may over- or underestimate the actual expenditure level in a given state. As such, this is a potential source of measurement error. When included in this study, military prime contract 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.

The average real dollar values of military prime contracts in millions of dollars in each state are described in table III-1, and figure III-1 plots these numbers graphically after normalizing with state population. Figure III-1 shows that states with more than \$734 per state capita in contract value (black shaded areas) include California, Texas, Washington, Alaska, and Virginia. Contrary, Montana, Nebraska, Oregon, and South Dakota are among areas with relatively few military dollars per person (white shaded areas). As a result of this large difference in military prime contract values in different states there may be important differences in the economic responses to a military prime contract shock. This topic will therefore be further analyzed.

Labor productivity data have been computed by taking the natural logarithm of real gross domestic product by state which was first divided by state employment. Gross domestic product by state is from the Bureau of Economic Analysis Regional Economic Accounts, and employment numbers are total non-farm employment by state from the Bureau of Labor Statistics Current Employment Statistics survey. The aggregate GDP deflator was used to convert nominal variables into real terms. Census estimates of state population, downloaded from the Bureau of Economic Analysis' website, are used when the data are normalized by population in some graphs. 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 paper 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 United States Patent and Trademark Office (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, the paper chooses to focus on the sample period 1967-1995 which includes the Carter-Reagan military buildup. All series enter in log-levels. In the analysis, the following notation is used as abbreviations: Military prime contracts are denoted by MPC, real gross domestic product by state is abbreviated to RGSP, and EMP denotes employment. In addition, LP denotes labor productivity, while PAT denotes patent applications.

The following analysis examines the economic effects of an increase in military prime contract 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 military prime contract

awards at the state level of spatial disaggregation 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.

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.

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

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

$$\text{and } E(\varepsilon_{nt} \varepsilon_{rs}') = \begin{cases} \Omega & \text{for } n = r, s = t \\ 0 & \text{otherwise} \end{cases} \quad \text{for } t = 1, \dots, T \text{ and } n = 1, \dots, N.$$

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-

⁵ Mayer (1991) page 210.

specific effect which is constant across time but varies across regions. This allows for individual effects that influence the states differently. 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:

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

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 paper estimates this system by OLS. In general, under the assumption of a fixed T and $N \rightarrow \infty$, 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. Next, the paper estimates the effect of a military prime

contract shock on various economic indicators and on patents which are a measure of the development of new technological advances.

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 $p = 3$ 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 military prime contracts of each region to be affected by contemporaneous changes in economic and technological indicators such as gross state product, employment, or the technological advances made in the given area. Standard errors are estimated by Monte Carlo with 2000 simulations.

III.E. Empirical results

The paper now presents impulse response functions from bivariate PVARs. In the impulse response figures, the horizontal axes correspond 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-2 uses the newly available data on real gross state product, RGSP, to find that an MPC shock leads to a significant and long-lasting increase in RGSP a few years following 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-2, it can also be seen that an increase in RGSP only has a small positive effect on MPC awards after several years. This indicates that military prime contracts are not primarily awarded to states with good economic conditions. Specifically, there is no evidence of military prime contracts 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 military prime contracts are not allocated based on state economic activity.

The response of employment to a military prime contract shock is depicted in figure III-3. As was the case with real gross state product, military prime contracts lead to a significant increase in employment after a lag of several years. This increase in employment is consistent with results found by Hooker and Knetter (1997) and Davis, Loungani, and Mahidhara (1997). But the positive effects on both RGSP and EMP are similar in the sense that labor productivity, LP, defined as output per employed worker, mainly responds insignificantly positive to an MPC shock. This is depicted in figure III-4 when using both 2 and 3 lags in the PVAR. Figure III-3 indicates that military prime contracts may increase in the long run after an increase in employment. However, figure

III-4 reinforces the result from RGSP that defense spending is not awarded based on state productivity.

In order to examine if military prime contracts lead to the development of new technology, the paper estimates the system with patent application data as a measure of technological progress. Figure III-5 illustrates how the development of new technology is distributed across the United States by using information on the average annual number of patents per thousand people in each state. States with many patents per person include California, Minnesota, and several states in the North East area of the U.S., while North and South Dakota as well as Arkansas, Mississippi, and Alabama are areas with relatively few patents. When comparing this plot of the U.S. with figure III-1, it can be seen that there is no clear connection between states with large military prime contracts and states with many patent applications. For example, Alaska receives relatively many military contract awards when taking into account state population, while Alaska is in the bottom quintile in figure III-5, corresponding to a relatively low number of new technologies developed. Since the variance of military prime contract awards across the 50 states and the District of Columbia is high, it is of interest to separately examine states with many or few military contracts. Therefore, section III.F below examines the empirical results when only certain subgroups are considered.

To estimate the effect on the development of new technology of a military expenditure shock, the patent variable, PAT, is ordered first in the system as it is expected to take time to develop a new technology. This also allows for military prime contracts to be awarded to areas with technologically advanced production. Figure III-6 depicts the results from this estimation, using both 2 and 3 lags. Indeed, the paper 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 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 had been made as a result 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 also 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) have examined this issue. They found that the surge in patenting can be interpreted as a surge in overall U.S. scientific development. The working hypothesis in this paper 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 paper 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-7. Two lags are included as a result 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 military prime contract 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-7 confirms that military prime contracts 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-8 displays the responses to an MPC shock in a PVAR with PAT, RGSP, and MPC. When controlling for real gross state product, the positive response of patents to an MPC shock remains significant. Also the response of RGSP to an MPC shock is significantly positive with long-lasting effects.

Figure III-9 reports the results from a PVAR with PAT, EMP, and MPC, using both 2 and 3 lags. As was the case in the bivariate systems, an MPC shock leads to an increase in both patent applications and employment. However, the shape of the patent impulse response function is somewhat sensitive to the number of lags included in the system as the response of PAT estimated with three lags becomes significant shortly after the shock while the corresponding response function estimated with two lags tends to increase over time. The corresponding results from a PVAR with PAT, LP, and MPC are shown in figure III-10. Patents continue to respond positively and the result is robust to changing the lag length. Additionally, as was the case in the bivariate systems, the response of labor productivity is insignificantly positive. When three lags are included,

the lower left panel of figure III-10 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 2 lags.

III.F. Subgroups of states

As seen from figure III-1, the 51 regions receive very different amounts in military prime contracts per person. Panels A and B of figure III-11 display graphically the distribution of military spending which has been sorted based on average annual real military spending and divided into quintiles. Figure III-11, panel A, displays the distribution when sorted based on real military prime contract awards by state population and panel B reports the corresponding graph without normalizing by population. The number printed on each state in the figure corresponds to the state ranking of average annual real MPC. In panel A of figure III-11, Idaho is marked number 1 and the District of Columbia number 51, corresponding to the areas with the lowest and highest MPC amount per person, respectively. The two figures show very similar patterns with Alaska and Hawaii as a few exceptions.

In order to examine subgroups of states, this paper follows the grouping method used by Hooker and Knetter (1994) and sorts the areas based on military prime contract awards normalized by state population. This grouping is shown in table III-2, and table III-3 provides the average annual real MPC dollar values and standard deviations within each quintile both with and without normalizing by state population. As described in table III-3, the average annual contract amount per person varies considerably between

quintiles as quintile 5 on average receives contract amounts of an order of magnitude larger than the corresponding contract awards in quintile 1. The standard deviation of average annual MPCs within quintile 5 is large compared to the mean value. This is a result of not normalizing with population as California on average receives more than \$27 billion per year in military prime contracts, while Maryland, being the state in quintile 5 with the lowest dollar value of contracts, receives around \$4 billion in an average year. As mentioned, the grouping for the following analysis is based on normalizations with state population.

Figures III-12 through III-15 display the responses of RGSP, 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-12 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 how aggregate effects found in figure III-2 mainly occurred as a result of economic consequences for the small military states of an increase in military spending. However, figure III-13 plots how employment 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 employment in quintile 2 does become significant in the long run if 1, 4, or 5 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 to a greater extent be positively

affected by a military shock 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-14 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 military prime contract award, again clearly indicating how subgroups within the U.S. are affected differently.

Figure III-15 reports the results from bivariate patent analyses for each quintile. Quintiles 1 and 2 are again positively affected, indicating that new technology is being developed as a result of the prime contracts. Interestingly, the states that experience increased labor productivity after an increase in military prime contracts are therefore also states that develop more new technology. Comparing figures III-1 and III-5, there is no clear connection between the amount of military spending received and the intensity of patenting. Both North and South Carolina are contained within MPC quintiles 1 and 2 and perform relatively little patenting. However, Kansas, Mississippi, and Maine have correspondingly few patents, while receiving military prime contract awards per person equivalent to being in MPC quintiles 4, 5, and 4, respectively. Among the larger military states, quintile 3 and 5 tend to do less patenting after an MPC shock, while quintile 4

responds insignificantly positively. If 1 or 4 lags are included in the PVAR (not shown), then quintile 4 does respond significantly positively.

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 which 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 paper help to understand how aggregate U.S. economic effects occur as a result of underlying regional fluctuations. Existing studies that have focused on the U.S. as an aggregate have reported different economic effects of defense spending. On the contrary, this present paper with more degrees of freedom 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 as a result of defense contracting. This may partly be a result of the research and development contracts that are inherent in the aggregate military prime contract numbers. Furthermore, these findings correspond to the results found in the previous chapter. Chapter II showed that large military prime contractors increase company sponsored research and development after a military prime contract award, indicating that indeed new technology is being developed.

III.G. Conclusion

This paper 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 therefore provided variation in the data series. Furthermore, the dollar amount of military prime contract awards varies considerably across states as does the annual amount of patenting.

Using U.S. data on military prime contract awards, gross state product, employment, and patenting from 1967 to 1995 for the 50 states and the District of Columbia, the paper 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 military prime contract shock. However, these positive responses are close in magnitude, leading to insignificant effects on state labor productivity. Patents increase strongly after increased military spending, providing evidence that new technology is being developed as a result of the increased expenditure.

Next, the paper 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 how U.S. macroeconomic results are not found evenly across the country.

Acknowledgement: I thank Bryan D. Goudie for co-authoring this chapter. The dissertation author is a primary author of this chapter.

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

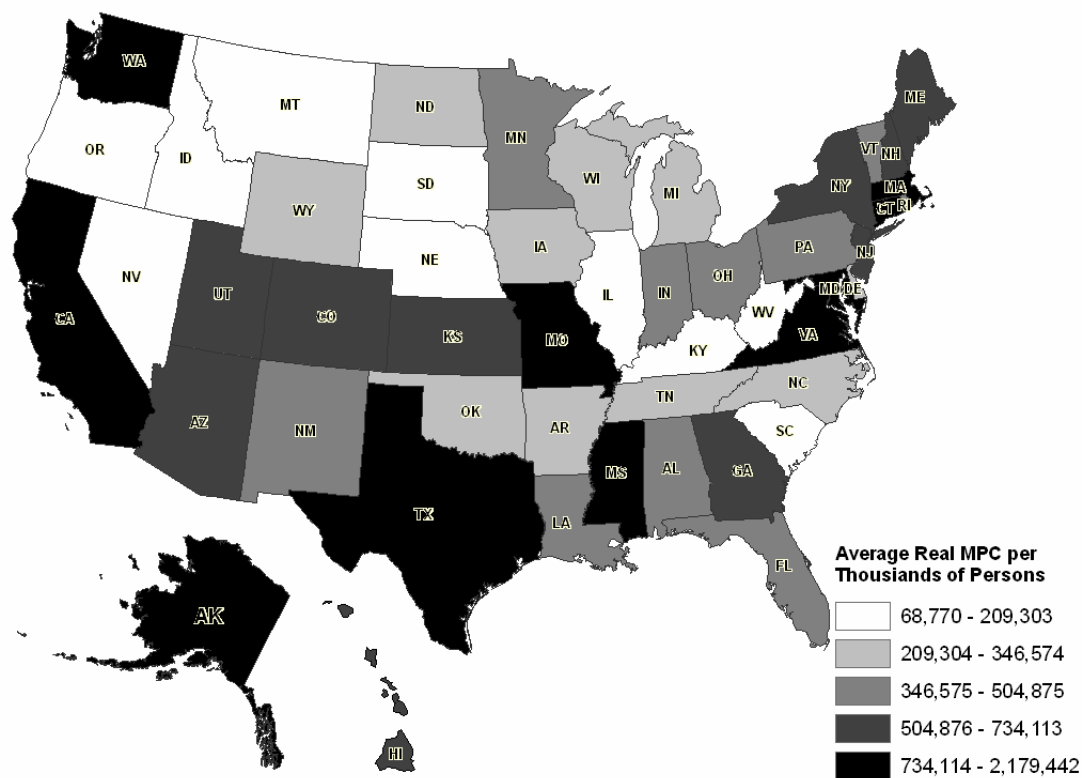
Table III-3: Average dollar value of MPC

Quintile	Average MPC per person		Average MPC, millions	
	Mean	Standard deviation	Mean	Standard deviation
1	146	43	164	70
2	263	48	533	115
3	440	45	1,225	376
4	592	70	2,539	674
5	1,213	466	8,398	6,684

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 III-1.

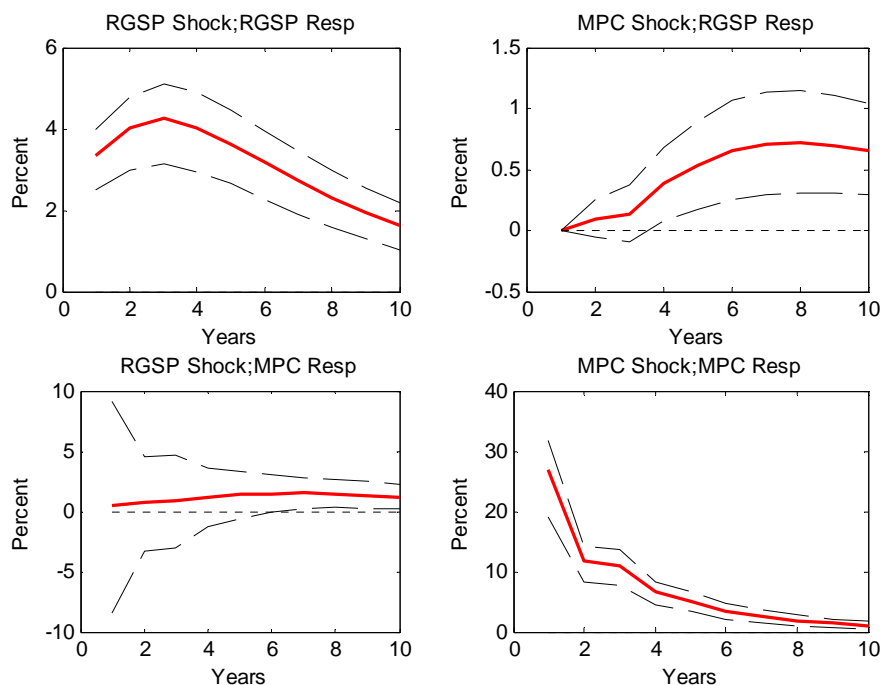
The left hand columns are normalized by state population, and means and standard deviations are denoted in 2000 dollars.

The right hand columns are not normalized by population, and means and standard deviations are here denoted in millions of 2000 dollars.



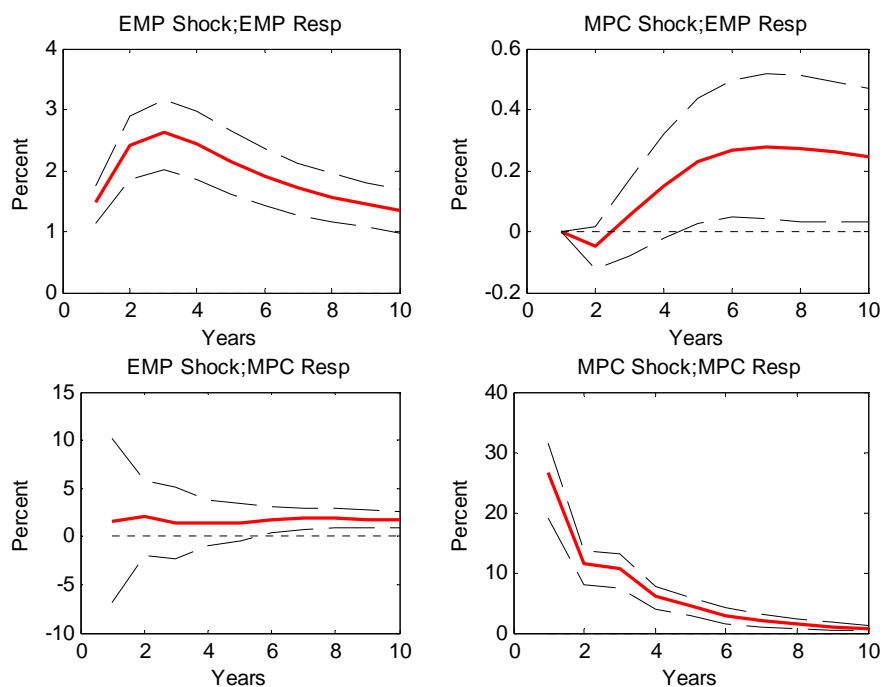
Note: The grouping is based on average annual real MPC per thousand people, using data from 1967 to 1995. 10 states are included in each of the first 4 groups, while 10 states and the District of Columbia enter in the group, indicated with black.

Figure III-1: Regional military prime contract awards per person



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.

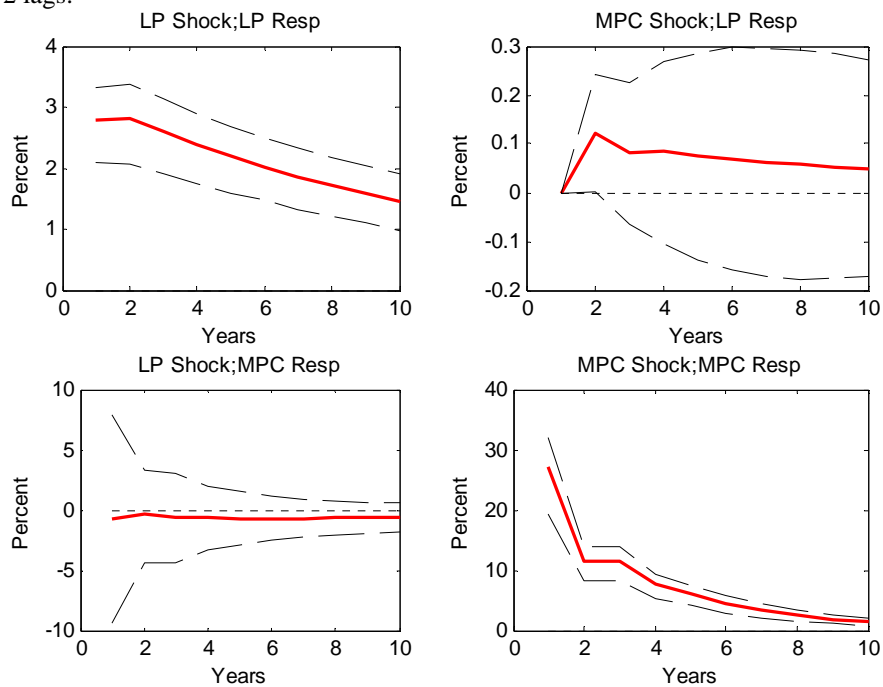
Figure III-2: Bivariate PVAR with RGSP and MPC



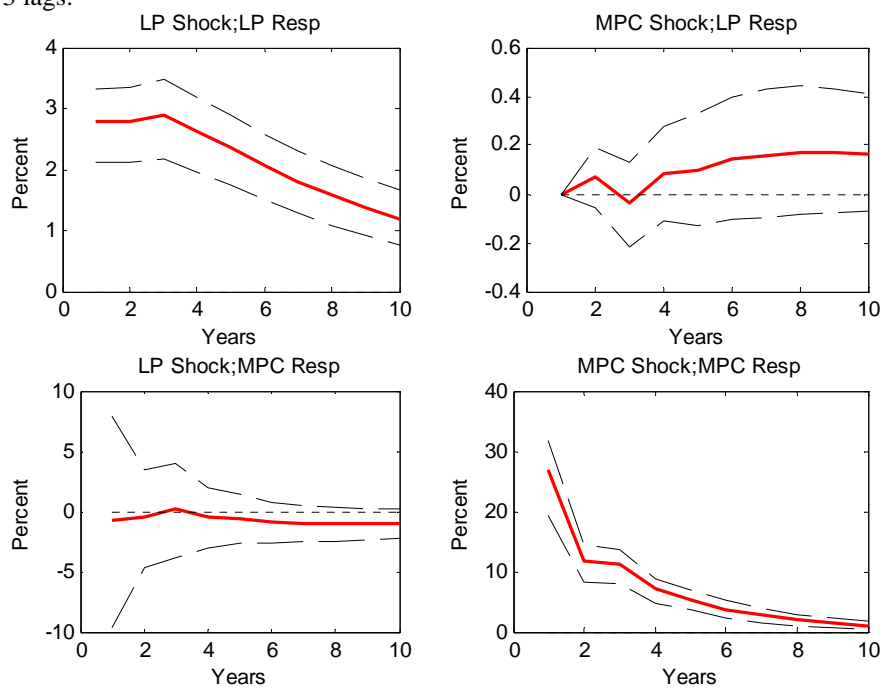
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 3 lags are included.

Figure III-3: Bivariate PVAR with EMP and MPC

2 lags:

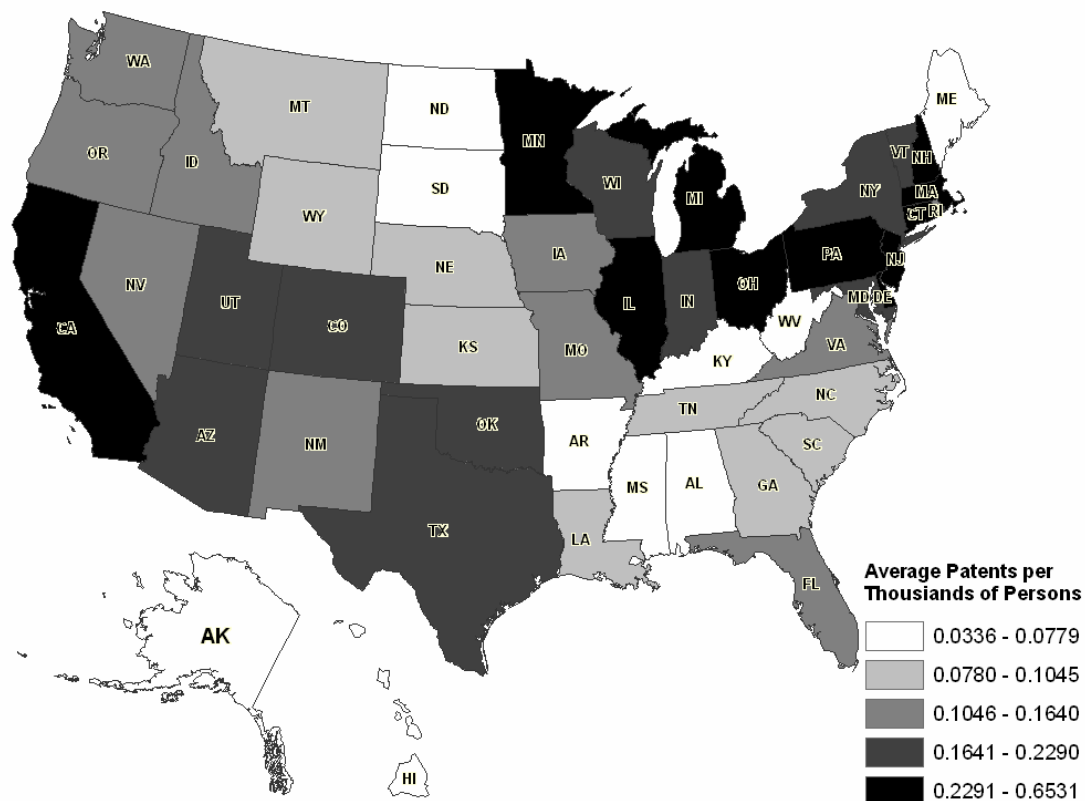


3 lags:



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.

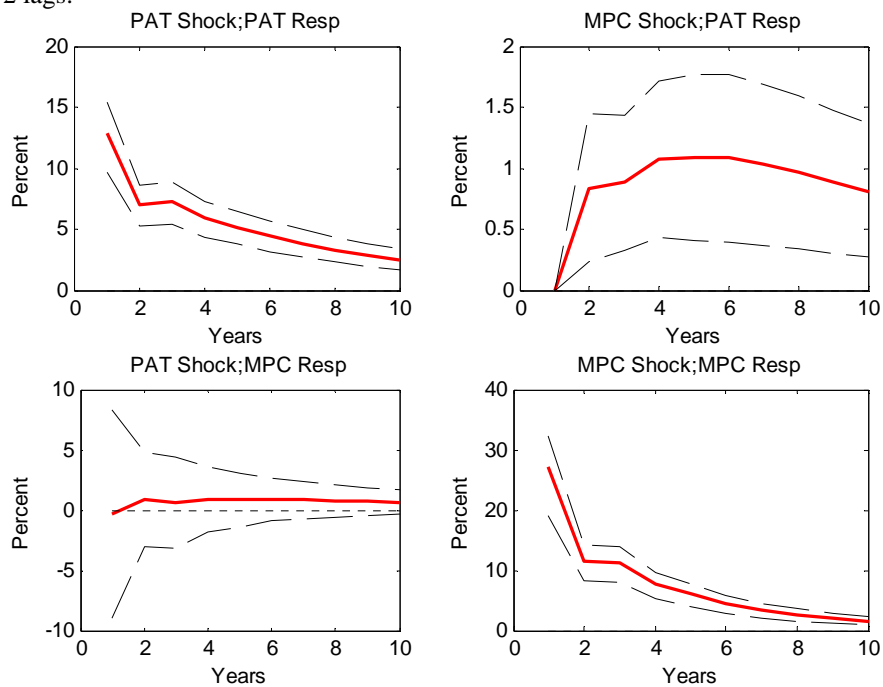
Figure III-4: Bivariate PVAR with LP and MPC



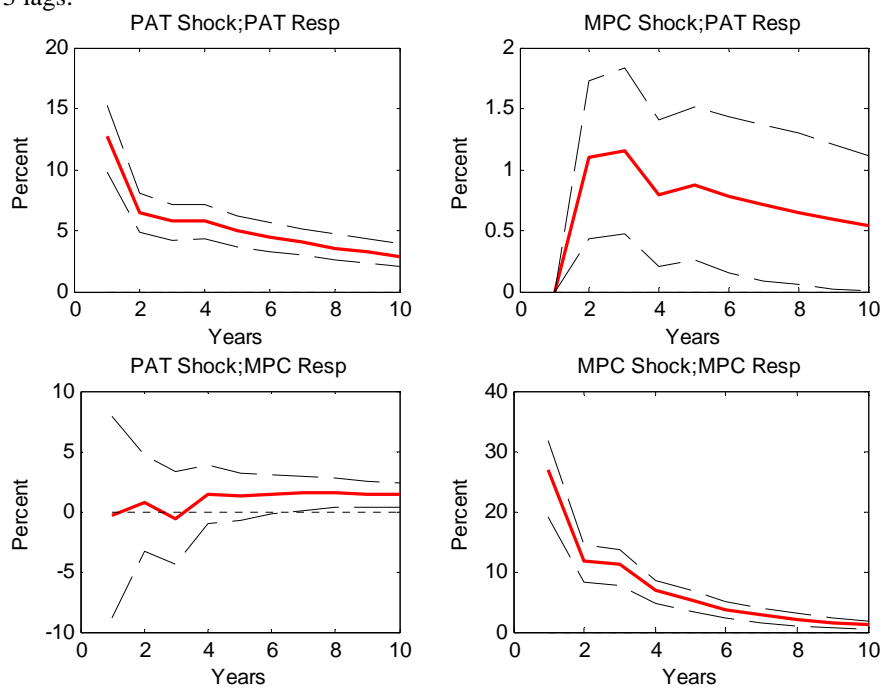
Note: The grouping is based on average annual number of patents, sorted by application year, per thousand people in the given state or district, using data from 1967 to 1995. 10 states are included in each of the first 4 groups, while 11 states enter in the group indicated with black.

Figure III-5: Regional patenting

2 lags:

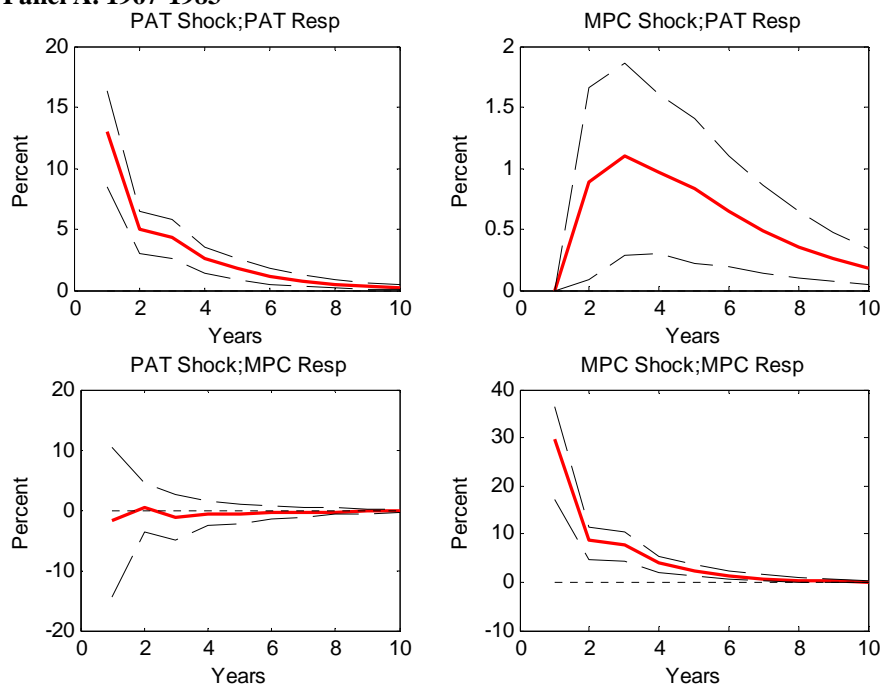
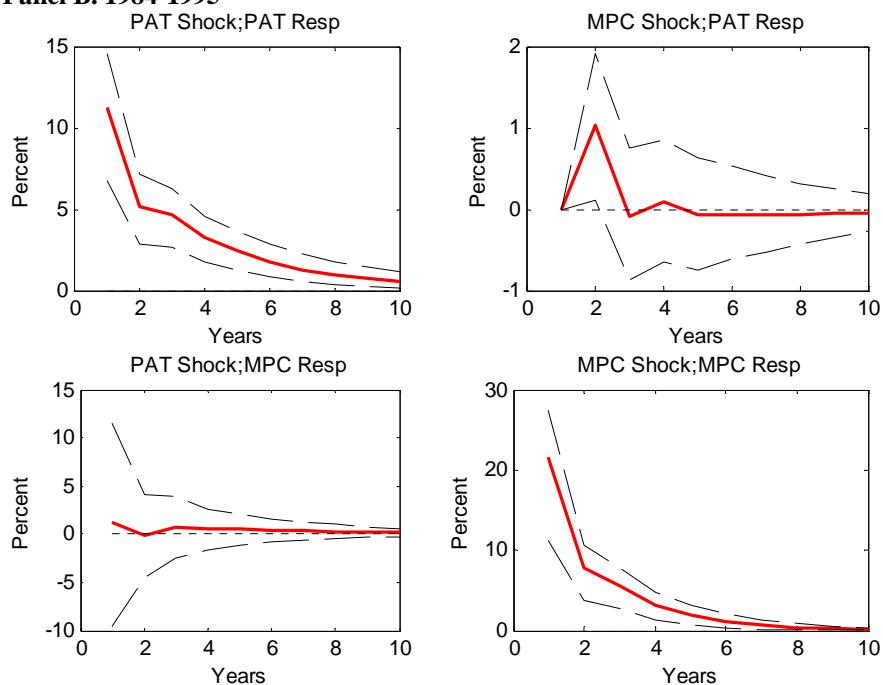


3 lags:



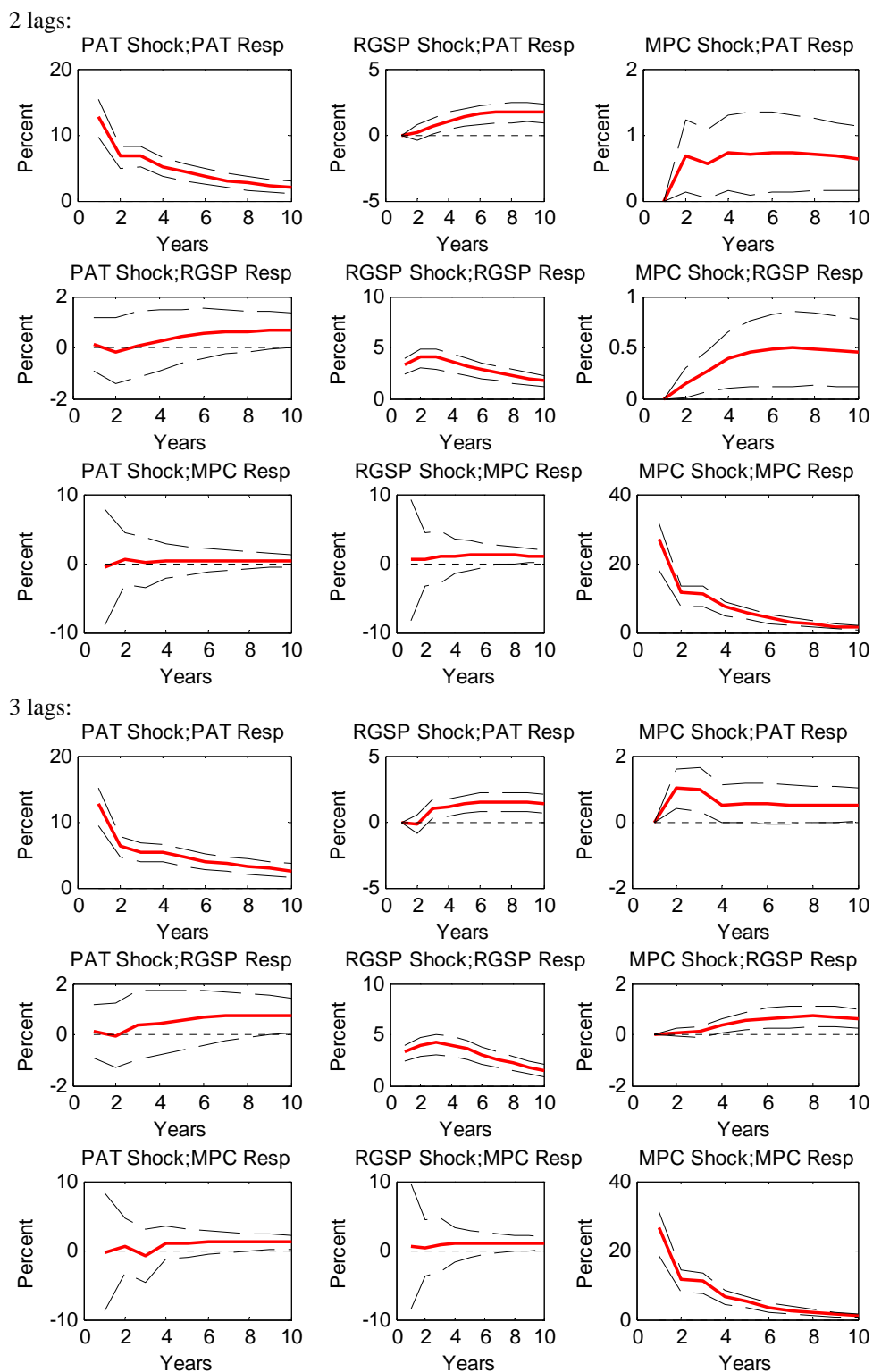
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals.

Figure III-6: Bivariate PVAR with PAT and MPC

Panel A. 1967-1983**Panel B. 1984-1995**

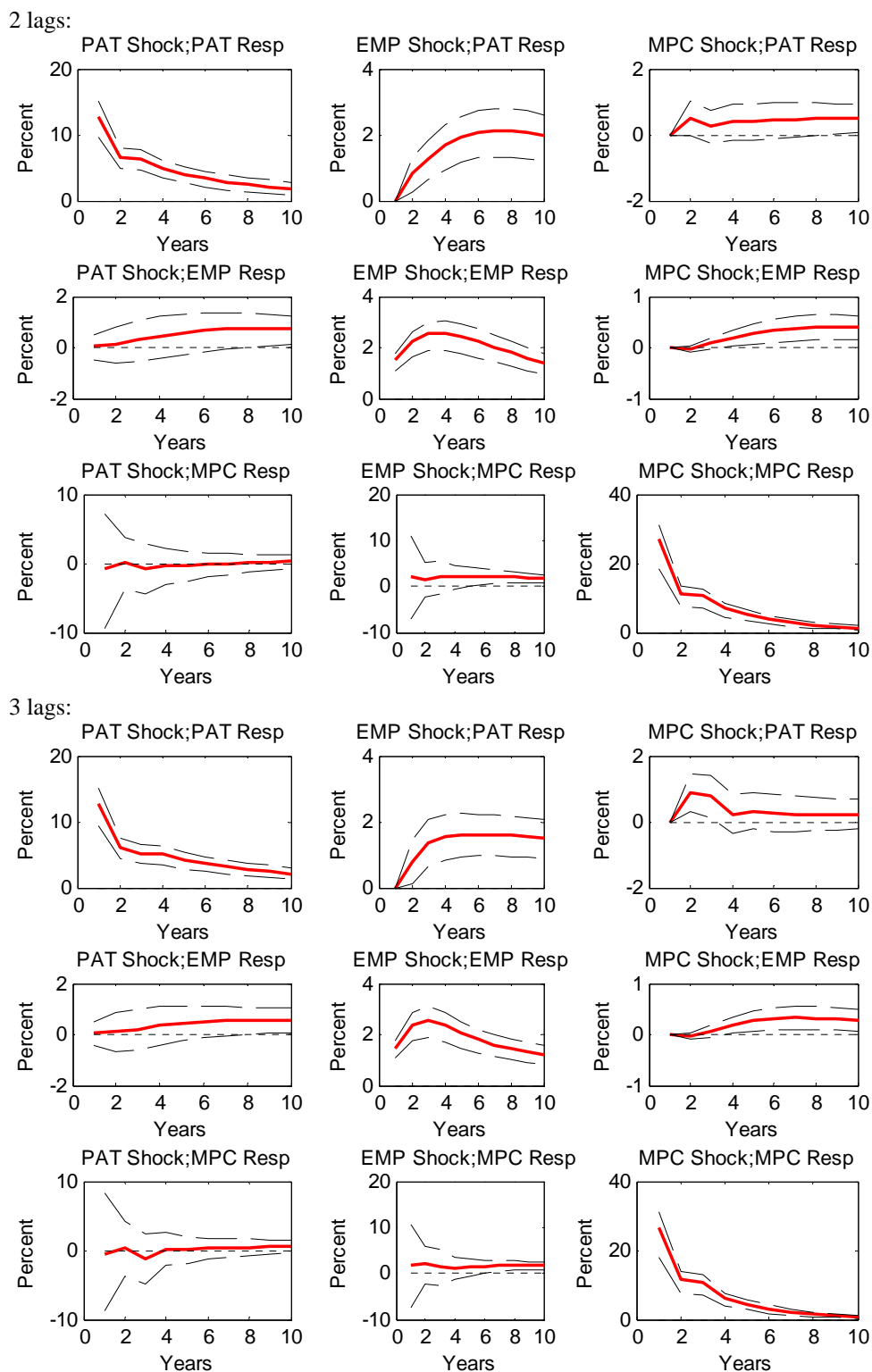
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 2 lags are included.

Figure III-7: Bivariate PVAR with PAT 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.

Figure III-8: Trivariate PVAR with PAT, RGSP, 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.

Figure III-9: Trivariate PVAR with PAT, EMP, and MPC

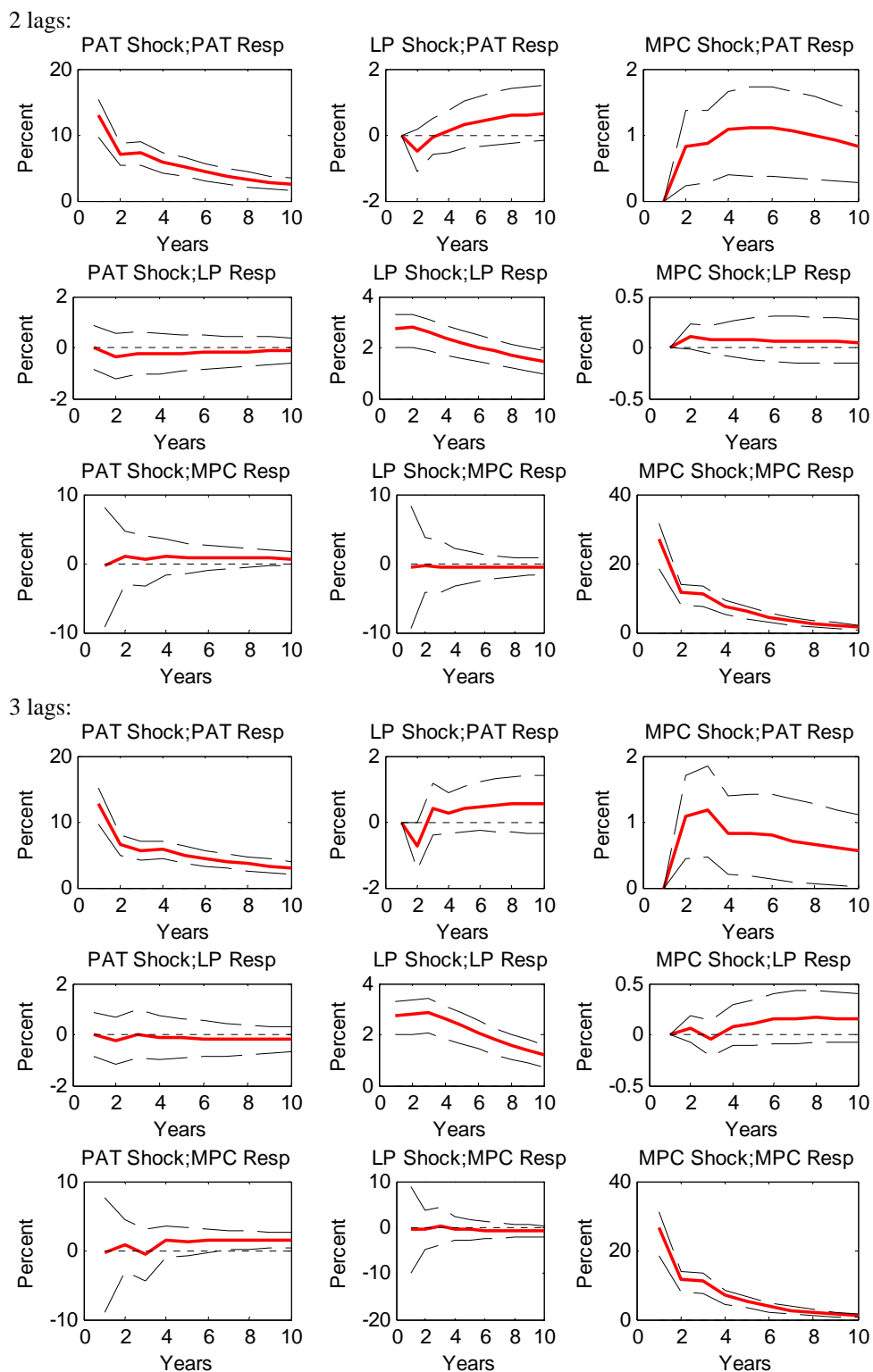
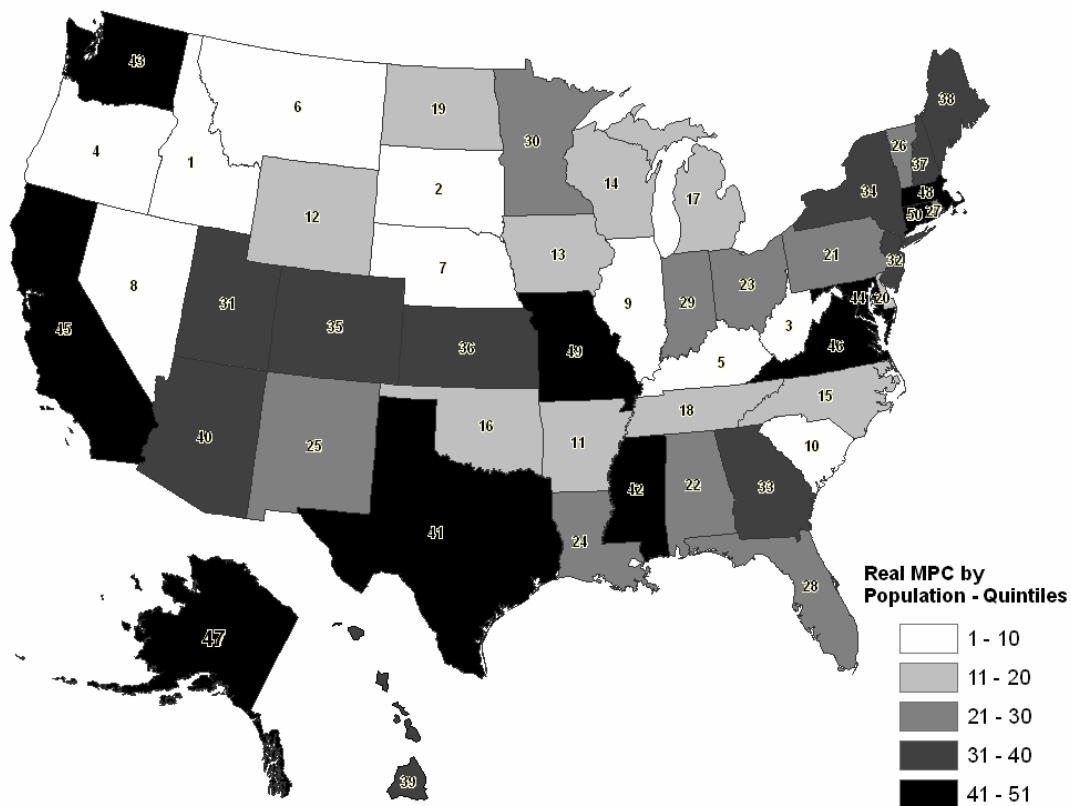


Figure III-10: Trivariate PVAR with PAT, LP, and MPC

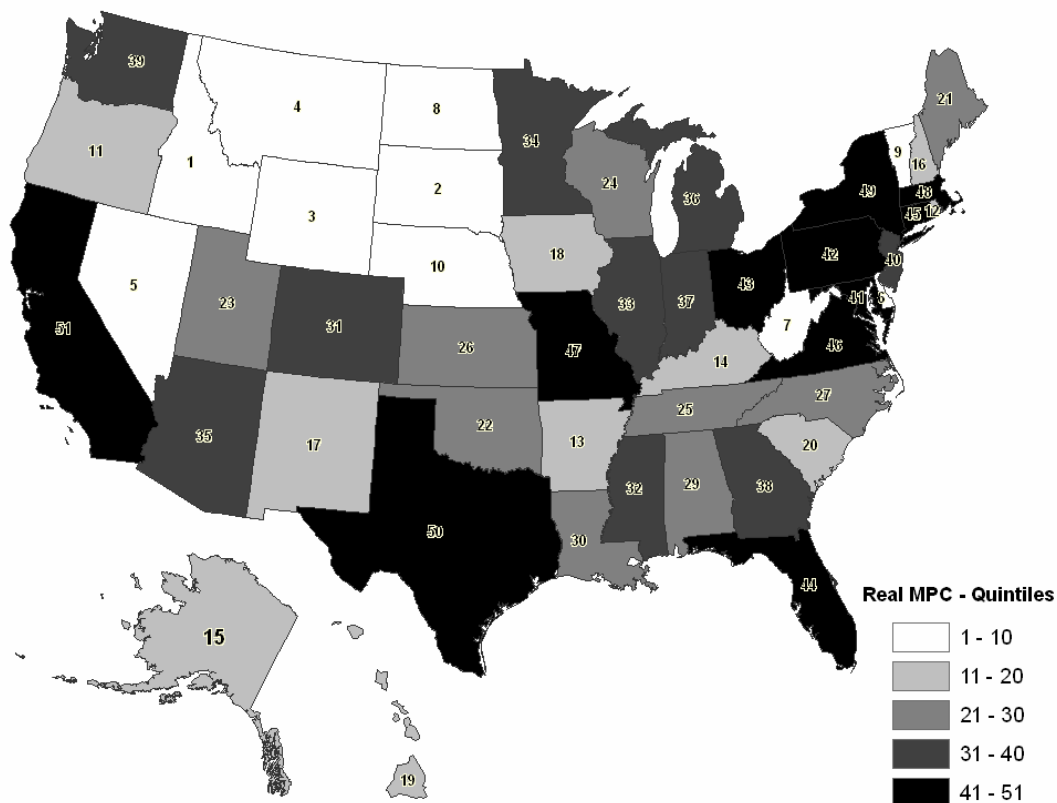
Panel A. Military prime contract awards per person



Note: The grouping is based on average annual real MPC per thousand people, using data from 1967 to 1995. 10 states are included in each of the first 4 groups, while 10 states and the District of Columbia enter in the group indicated with black.

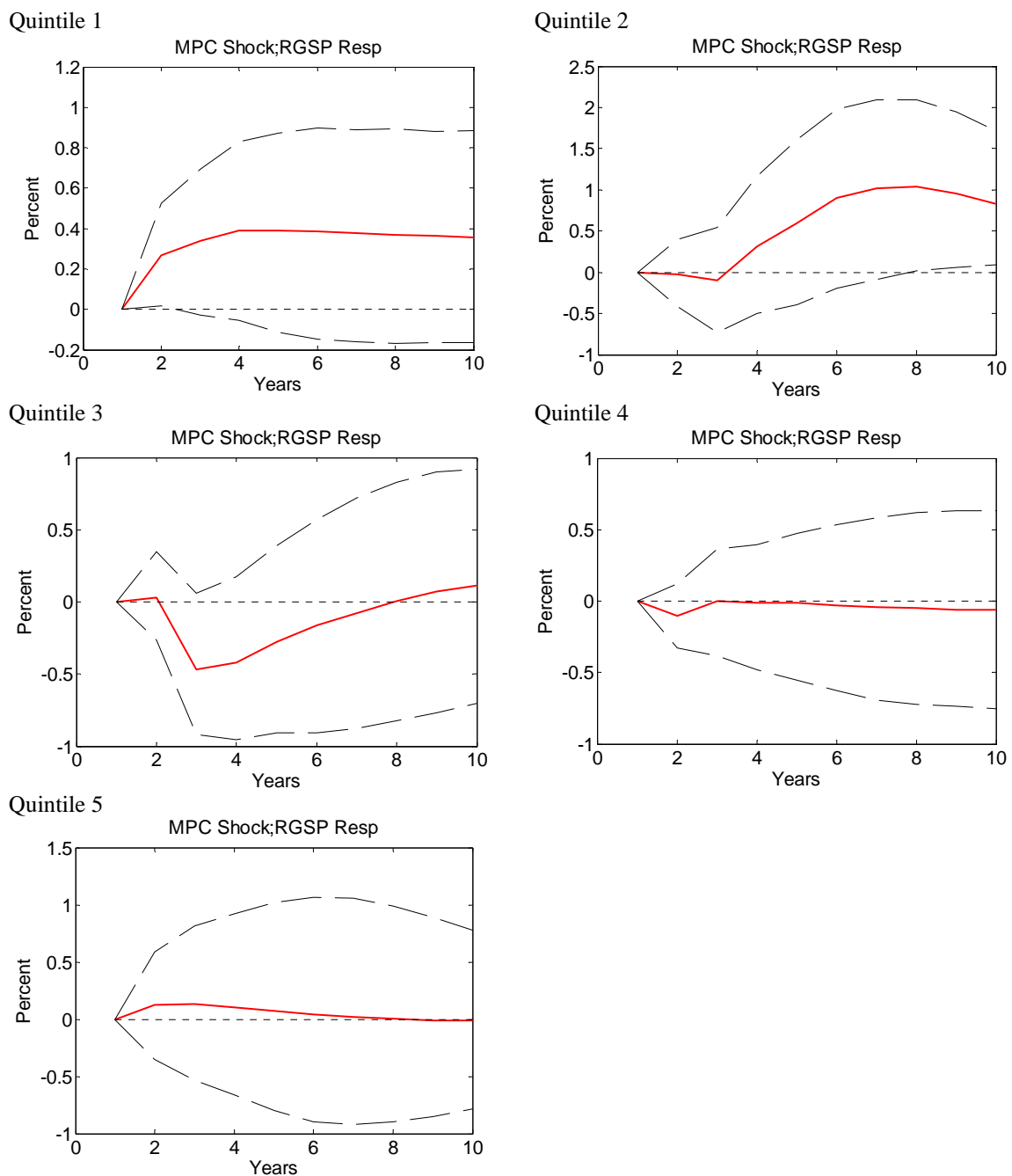
Figure III-11: Regional military prime contract awards, quintiles, continued on next page

Panel B. Military prime contract awards, not normalized by population



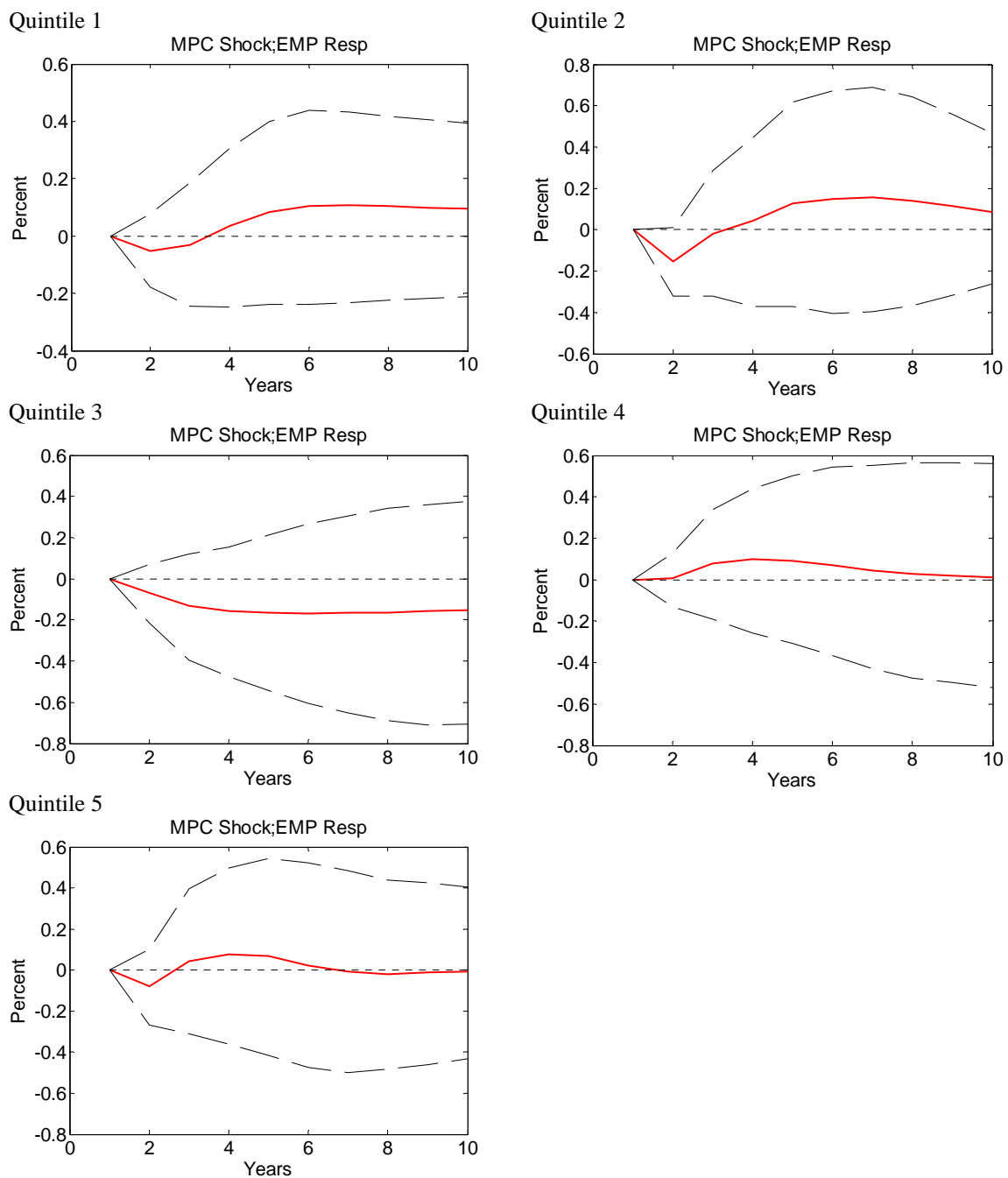
Note: The grouping is based on average annual real MPC, using data from 1967 to 1995. 10 states are included in each of the first 4 groups, while 11 states enter in the group indicated with black.

Figure III-11 (continued): Regional military prime contract awards, quintiles



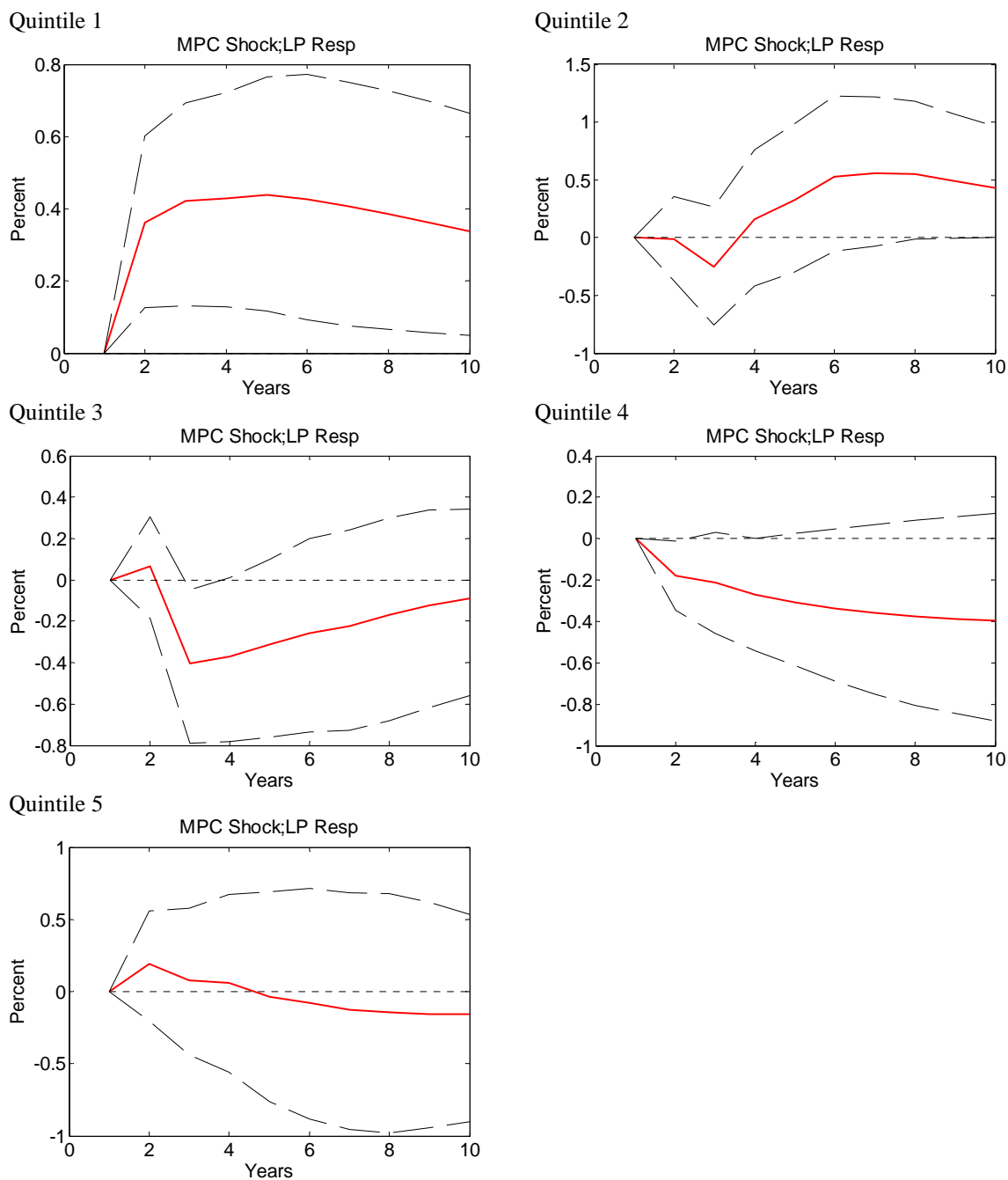
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 3 lags are included.

Figure III-12: Bivariate PVARs with RGSP and MPC for the five subgroups



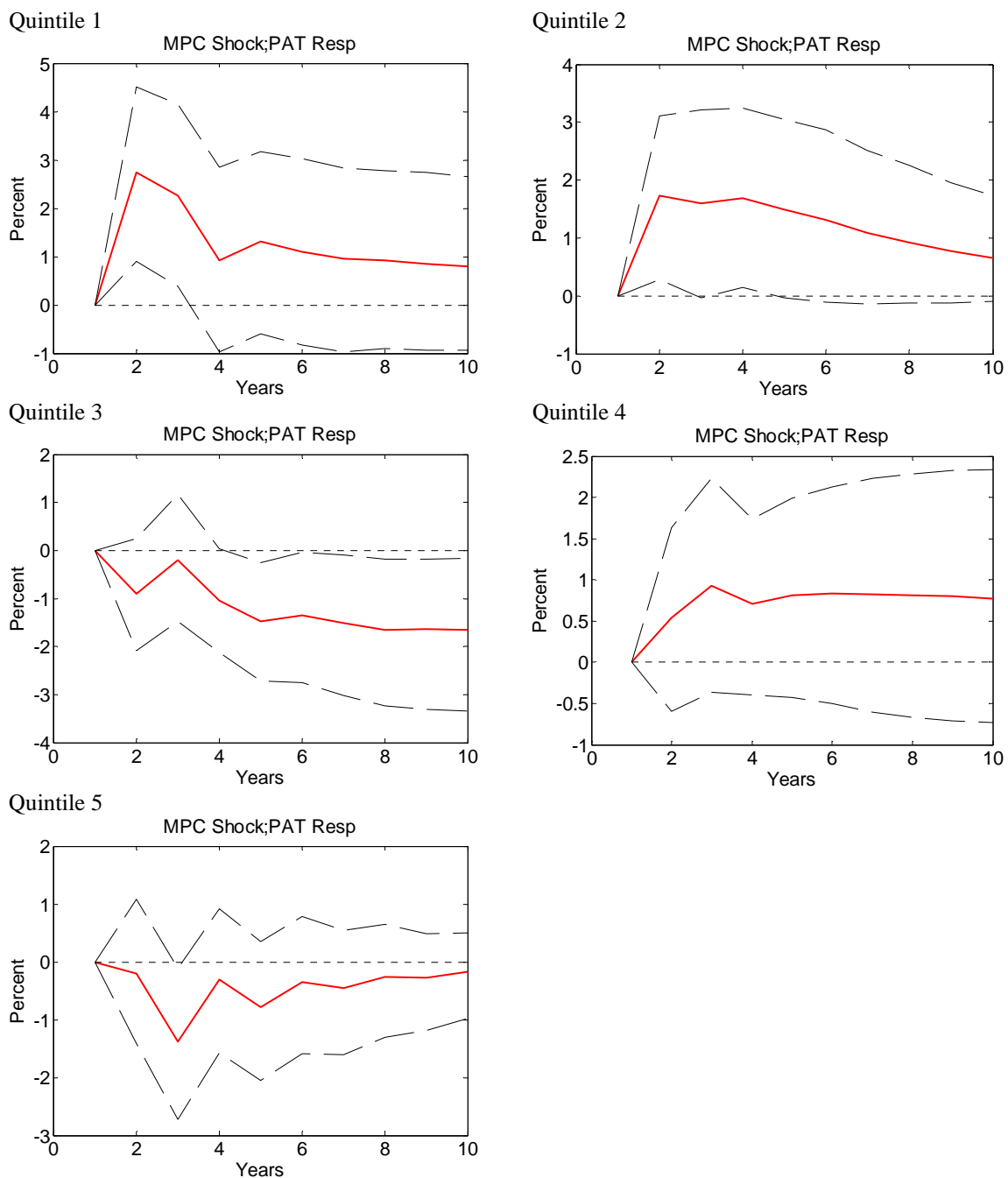
Note: The horizontal axis denotes the forecast horizon in years. Year 1 is the time of the shock. The dashed lines are 90 percent confidence intervals. 3 lags are included.

Figure III-13: Bivariate PVARs with EMP and MPC for the five subgroups



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.

Figure III-14: Bivariate PVARs with LP and MPC for the five subgroups



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.

Figure III-15: Bivariate PVARs with PAT and MPC for the five subgroups

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