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Entrepreneurship and Economic Growth: The Proof Is in the Productivity

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ENTREPRENEURSHIP AND ECONOMIC GROWTH: THE PROOF IS IN THE PRODUCTIVITY

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Abstract

Popular and policy discussions have focused extensively "entrepreneurship." While entrepreneurship is often viewed from the perspective the individuals' benefits—an increase in standard of living, flexibility in hours, and so forth—much of the policy interest derives from the presumption that entrepreneurs provide economy-wide benefits in the form of new products, lower prices, innovations, and increased productivity. How large are these effects?

Using a rich panel of state-level data we quantify the relationship between productivity growth—by state and by industry—and entrepreneurship. Specifically, we use state-of-the-art econometric techniques for panel data to determine whether variations in the birth rate and death rate for firms are related to increases in productivity.

We find that shocks to productivity are quite persistent. Thus, to the extent that policies directly raise labor productivity, these effects will be long lasting. In addition, the data reveal that increases in the birth rate of firms leads, after some lag, to higher levels of productivity, a relationship reminiscent of Schumpeterian creative destruction. Given previous evidence that government policies raise the rate of entry of new entrepreneurs, our findings link these policies to enhanced productivity.

1. Introduction

In recent years, entrepreneurs have been the focus of considerable popular discussion. In part, this fascination has reflected the individuals' interest in "how to get ahead" see, e.g., Holtz-Eakin, Rosen, and Weathers (2000). However, a substantial part of the popular and policy interest has been in the links between entrepreneurs' activities and overall economic performance. For example, testifying several years ago at a congressional hearing on "the entrepreneurial spirit in America," Wisconsin's Senator Robert Kasten said of entrepreneurs: "They create new jobs. They provide new competition to existing businesses. They help to improve product quality, help to reduce prices, add new goods and services never before thought of, advance new technologies, America's competitive stance." His statement captures the view that entrepreneurial enterprises are valuable sources of technological advance, jobs, and dynamism.

In this paper, we investigate the statistical links between measures of entrepreneurial climate and one aspect of economic dynamism: productivity. Our goal is to quantify the reduced-form link between increased entrepreneurial activity—indexed by firm entry and firm exit—and greater output per worker. To the extent that specific policies—lower marginal tax rates, enhanced infrastructure, reduced regulatory barriers—may be shown to increase the ability of entrepreneurs to enter new markets, this link will provide insight into one aspect of the benefit-cost tradeoff of such policies.

Of course, as the statement by Senator Kasten indicates, productivity is a small aspect of the overall impact of entrepreneurs. Even if one finds little link with productivity, the virtues of competitive pressure on product pricing, product variety, and other aspects of performance should not be overlooked.

The remainder is organized as follows. In Section 2 we briefly lay out our strategy for analyzing the data. Section 3 is devoted to data description, after which we turn to econometric issues. In Section 5 we present the results of analyzing two rich panel data sets, one providing state-by-state information and the other focused on industry-level analysis. The concluding section contains a summary. We find that shocks to productivity are quite persistent. Thus, to the extent that policies directly raise labor productivity, these effects will be long lasting. In addition, the data reveal that increases in the birth rate of firms leads, after some lag, to higher levels of productivity, a relationship reminiscent of Schumpeterian creative destruction. Given previous evidence that government policies that improve access to capital (Holtz-Eakin, Joulfaian, Rosen 1994a, 1994b) or reduce tax rates (Bruce 1999; Gentry and Hubbard 2000) raise the rate of entry of new entrepreneurs, our findings link these policies to enhanced productivity.

2. Analytic Strategy

Policymakers care about the standard of living, but their choices affect this only indirectly through their impact on new firm formation, expansions, and shutdowns. Thus, while we are ultimately interested in the effects of public policies, our approach herein is to focus on the dynamic interrelationships among births, deaths, and productivity.

Our approach is unabashedly empirical, in large part because the wide variety of existing theoretical models provides a paucity of empirical guidance. For example, in the model of Jovanovic (1982), entry of new entrepreneurs is driven by *expected* ability (productivity) and profits. However, entrepreneurs' experience allows them to learn about their true ability and the less able choose to exit. Accordingly, entry may be associated with either higher *or* lower productivity, while exits are associated with an increase in productivity.

More generally, Johnson and Parker (1994) identify two possible dynamic linkages between birth rates and death rates. In the first, births lead to additional births and increases in deaths spawn deaths. The foundation of this relationship is essentially Keynesian (particularly in a regional context) in which the birth or death of a firm sets off a chain reaction of related actions due to inter-industry relationships. While this gives predictions regarding the level of activity, it provides no particular restriction on the productivity effect.

The second effect is Schumpeterian creative destruction. An increase in the birth rate will "cause" firm deaths. Indeed, given the well-established high failure rate of new firms (see Gibb 1990) some of the deaths may be the entering firms. At the same time, new more productive firms are replacing inefficient competitors, thereby implying that productivity is higher. In the context of creative destruction, changes in the death rate have an indeterminate effect. It could reflect reduced competition—and concomitant lower productivity—or it might be indicative of reduced entry barriers (i.e., fewer new firms fail). In the latter scenario, greater competition and productivity pressure would prevail.

Given the wide range of possible outcomes, it appears that the most fruitful tact is to turn to empirical work.

3. Data

Our goal is to analyze the relationships among productivity, and measures of entrepreneurial activity, at both the state and industry level. To begin, we compute productivity at the state level as Gross State Product (GSP) per worker. Real GSP data (in millions of chained 1996 dollars) are available from 1986 to 1998 from the Bureau of Economic Analysis.[1] Employment is the number of full- and part-time workers taken from the Census' Regional

Economic Information System (REIS). In contrast, for our industry-level analysis we employ data available for major industries from 1969 to 1997 as provided by Bureau of Labor Statistics.

In each case, we divide real GSP by employment, to yield productivity for 50 states and 9 major industries: agriculture; mining; construction; manufacturing; transportation, communications, and public utilities; wholesale trade; retail trade; finance, insurance, and real estate; and services.

The next issue concerns measures of "entrepreneurism." Although none is ideal, there are many potential indicators of an entrepreneurial climate. For purposes of this analysis, we focus on the rate of births, and the rate of deaths of firms.[2] It is hard to imagine an economic climate as "entrepreneurial" if new firms cannot enter. Similarly, an environment in which firms simply do not fail seems at odds with the competitive pressures provided by entrepreneurs.

To derive our measures, we divide the data on births by the number of establishments in place at the beginning year (and similarly for the death rate). Birth, death and establishment data are obtained from Small Business Administration, Office of Advocacy for the years 1990-1997. The data are available for all states and major industries.[3]

4. Econometric Issues

Consider the following dynamic panel model with predetermined variables, $y_{i,t-1}$, and exogenous variables, x_{it}:

$$y_{it} = \rho y_{i,t-1} + \beta' x_{it} + \mu_i + v_{it} \tag{1}$$

where μ_i is the individual effect and v_{it} is the error term. Because the dynamic panel model includes a lagged dependent variable, the usual within group estimator is inconsistent if the time dimension is small (e.g., Nickell 1981). Several consistent estimators have been proposed for the dynamic panel model when the time dimension is small. A standard approach is to use by generalized method of moments (GMM), first-differencing the equation to remove the individual effect, μ_i, and then using lagged predetermined variables as instruments (see, e.g., Anderson and Hsiao 1981; Holtz-Eakin et al. 1988; Arellano and Bond 1991; and Ahn and Schmidt 1995). However, in dynamic panel models where instruments are weak, GMM has been found to have a large bias and large standard error, *e.g.*, Alonso-Borrego and Arellano (1999). Blundell and Bond (1998) pointed out that the weak instruments may come from two sources: (1) ρ is close to one and (2) the variance of the individual effect is large relative to the variance of v_{it}. In either event, the correlation between the instruments and predetermined variables will be wiped out It seems to us that the poor performance of the standard GMM may be expected if we have a short panel with highly persistent data and/or large variance of the individual effect. This seems quite likely to be the case in our setting. There is tremendous persistence in productivity, and both state and industries display considerable heterogeneity. Alternative approaches were proposed to address this weak instrument problem, e.g., Alonso-Borrego and Arellano (1999), and Blundell et al. (1999).

5. Results

We begin our investigation using the state-level panel, and then turn to a parallel analysis of our industry data.

5.1 Evidence from the States

We begin our analysis by summarizing the basic dynamics found in the three series of interest: productivity, births, and deaths. Specifically, we show in Table 2 state-by-state estimates of simple, AR(1) times-series models of each variable.[4] For example, the first row of the table shows that using our data yields an AR(1) coefficient for productivity in Alabama of 0.951, and an associated t-statistic of 3.92. Alternatively, estimating the time-series mode for the logarithm of productivity yields corresponding estimates of 0.931 and 3.89.

In short, the productivity data show substantial persistence. Consider, for example, the implications of an estimate of 0.95 for a one-time shock to productivity. With this degree of persistence, fully one-half of the original increase survives after over 13 years. Alternatively, the estimates imply that a higher initial *level* of productivity leads to only modestly slower subsequent productivity *growth*.[5]

Continuing across the first row, however, one finds a very different picture for the univariate behavior of births and deaths. Births, for example, have negative AR(1) coefficient (-0.621 or –0.636) while deaths show a positive coefficient indicating only mild persistence (0.438 or 0.432). In neither instance are the coefficients estimated with tremendous precision.

When taken as a whole, Table 2 suggests several observations. First, the choice of levels versus logarithms is of little import. The signs of the estimated coefficients always agree across these specifications, and the magnitudes are little affected as well.

Second, the AR(1) coefficients for productivity are nearly always positive. Only for North Dakota and Vermont do we find negative serial correlation. Similarly, only for Iowa and Utah are innovations in death rates negatively related; the remainder is positive. The sign of the estimated AR(1) coefficient for birth rates is often negative (80 percent of the estimates), but is positive 20 percent of the cases (ten states).

The final observation concerns the absolute magnitudes of the estimates. Recall from above that the key issue is whether the AR(1) coefficients exceed 1.0 in absolute value; that is, whether the univariate processes are stable. Looking over the estimates for the birth rate and death rate suggests little concern in this area.[6] However, the estimates for the productivity process suggest a mixture of states, some of which are characterized by non-stationarity. We pursue this further below.

At this juncture, we turn from the behavior of each data series in isolation to the dynamic interrelationships among productivity, births, and deaths. In doing so, we pool the observations for all states and seek to estimate relationships of the form[7]

$$y_{it} = \rho_1^y y_{i,t-1} + \rho_2^y b_{i,t-1} + \rho_3^y d_{i,t-1} + \mu_i^y + v_{it}^y \quad (2)$$

$$b_{it} = \rho_1^b y_{i,t-1} + \rho_2^b b_{i,t-1} + \rho_3^b d_{i,t-1} + \mu_i^b + v_{it}^b \quad (3)$$

$$d_{it} = \rho_1^d y_{i,t-1} + \rho_2^d b_{i,t-1} + \rho_3^d d_{i,t-1} + \mu_i^d + v_{it}^d \,. \quad (4)$$

In doing so, the primary issue is the econometric technique used to control for the state-specific effects in each equation. As noted above, the approach of Holtz-Eakin, Newey and Rosen—which we will refer to as the "panel data model" yields consistent estimates, but may suffer from poor small-sample properties due to weak instruments.

To get a feel for the issue, we present in Table 3, the estimates of the panel data model.[8] Consider first the estimates for the productivity equation at the top of the table. For purposes of comparison, we begin by estimating the analogue to Table 2; that is, we estimate the univariate relationship for (log) productivity using the HNR technique.

The point estimate of the AR(1) coefficient (0.008) is quite different from the estimates presented in Table 2. This suggests that the problem of weak instruments may be quite real in these data. Nevertheless, we continue to estimate the VAR(1) model for productivity. As shown in the second line of the table, productivity is positively related to lagged values of productivity (0.025), the birth rate (0.003), and the death rate (0.012). In each case, the estimate is statistically significant.

What do the data tell us about the remainder of the dynamic relationships? For the birth rate, past productivity predicts a lower birth rate (although the estimate, -0.004, is not statistically significant). In contrast, the lagged values of the birth rate and death rate have positive, statistically significant coefficients (0.144 and 0.094, respectively). Notice, however, that the panel data model estimates of the univariate AR(1) in the third line are again somewhat different that those in Table 2.

Finally, the last row of the table indicates that there is a positive and statistically significant relationship between lagged productivity growth (0.244), lagged birth rates (0.098) and lagged death rates (0.0168) in the data. Taken as a whole, the estimates in Table 3 are suggestive of significant and important dynamic interrelationships among the productivity, births, and deaths.

However, there remains a concern that the small sample properties of our estimates are less than desirable. Put differently, it may be desirable to estimate our parameters using the conventional "within" variation. Mechanically, this amounts to transforming each variable to deviations from the state-specific mean. While this has the advantage of eliminating the state-specific effects, it suffers from asymptotic inconsistency. In the absence of strongly correlated instruments, however, it may dominate the IV procedure in Table 3.

The outcome of this procedure is shown in Table 4.[9] The estimates paint a very different picture of the dynamics of interest. In particular, we now find that lagged values of the birth rate and death rate lead to lower productivity. Similarly, the VAR(1) estimates in the fourth row indicate that this estimation approach preserves the negative univariate relationship between birth rates and lagged birth rates. Past values of productivity and death rates, however, raise the birth rate. Finally, the last row of the table indicates that lagged values of the birth rate have a negative influence on future death rates. In short, the use of the within estimator leads to a very different characterization of the data.

How does one choose? Some guidance is provided by the univariate relationships also shown in the Table. In each case, the estimated parameter is closer in spirit to the range of estimates in Table 2 than the point estimate from the panel data model in Table 3. For this reason, we prefer the estimates found in Table 5 and focus on them in the remainder.

What do the estimates tell us about the implications of the underlying dynamics? Consider Figure 1, which shows the reaction of (log) productivity, birth rates, and death rates to a one-unit shock to productivity.[10] The top (dashed) line in the figures shows the evolution of productivity, and reflects the underlying persistence of productivity shocks. In reaction to a 1 percent shock, productivity is 0.75 percent higher in the following year, and remains 0.10 percent higher even after ten years. In contrast, the second (broken) line indicates that the birth rate rises by 0.40 percent subsequent to the productivity shock, but quickly decays. Finally, the solid line in the figure captures the fact that a productivity shock transitorily depresses the death rate of firms, although the effects are modest.

What does a similar exercise tell us about the impact of entry and exit on productivity growth? Consider Figures 2 and 3, which are laid out in a fashion analogous to Figure 1. As seen in Figure 2, a 1 percent increase in the birth rate of firms leads to a subsequent *decline* in future productivity, births, and deaths. However, the effects, in particular those on the evolution of measured productivity, are quite modest. The patterns contained in Figure 3 are a bit different. Here an increase in firm exits leads to a negative impact on future productivity—the quantitative magnitudes are fairly modest—but raises future death rates. The impact on births is initially positive, but turns mildly negative after three years.

5.2 Evidence from Industries

We turn now to the evidence provided by our panel data for industries at the national level. As with the state data, we begin with estimates of AR(1) times-series models of each variable for each industry.[11] The fourth row of Table 6 shows the estimates for the manufacturing sector using our data. The procedure generates an AR(1) coefficient of 1.11 (the t-statistic is 11.1). Alternatively, estimating the time-series mode for the logarithm of productivity yields an estimate of 1.08 (and t-statistic of 10.7).

Continuing across the row, however, one finds a very different picture for the births and deaths. Births, for example, have essentially no first-order correlation, while the estimates for deaths are more modest (roughly 0.5 in both specifications) and not estimated very precisely.

Again, rather than focus on each industry, we seek to assess the less on Table 6 as a whole. As with the states, the choice of levels versus logarithms is of little import. The signs of the estimated coefficients always agree across these specifications, and the magnitudes are little affected as well.

As with the states, the AR(1) coefficients for productivity are nearly always positive. Only for construction does there appear to be a negative first-order correlation. Similarly, only for the F.I.R.E. industry are innovations in death rates negatively related; the remainder is positive. The sign of the estimated AR(1) coefficient for birth rates is roughly evenly split between negative and positive, but is small in absolute magnitude. These patterns are reminiscent of our discussion of the state-level data (above).

As before, the final observation concerns the absolute magnitudes of the estimates. Among our estimated models for birth rates and death rates, there appears to be little suggestion of non-stationarity. However, the estimates for the productivity process suggest a mixture of possibilities.

We again turn from the behavior of each data series in isolation to the dynamic interrelationships among productivity, births, and deaths. However, because our cross-sectional size is so small, we do not attempt to estimate the panel data model. Instead, we turn directly to estimates based on the within variation. These are shown in Table 7.

The estimates paint an interesting picture of the dynamics of interest. In particular, again find that lagged values of the birth rate and death rate lead to lower productivity. The magnitudes, however, are quite small. In contrast to the state data, past values of productivity and death rates, lower (not raise) the birth rate. Finally, the last row of the table indicates that lagged values of productivity and the birth rate have a negative influence on future death rates.

What do the estimates tell us about the implications of the underlying dynamics? Again, we focus on Figures 4 to 6, which show the reaction of (log) productivity, birth rates, and death rates to a one-unit shock of each variable.[12] The top (dashed) line in the Figure 4 shows the evolution of productivity, and reflects the very strong underlying persistence of productivity shocks (the coefficient is just short of 1.0). In reaction to a 1 percent shock, productivity is 0.90 percent higher in the following year, and remains 0.50 percent higher even after 15 years. In contrast, the broken and solid lines indicate that the birth rate and death rate are both suppressed by the productivity shock, but the magnitude is quite inconsequential.

What about the effects of births and deaths on productivity growth? Consider Figures 5 and 6. As seen in Figure 5, a 1 percent increase in the birth rate of firms leads to a subsequent *decline* in future productivity, but (after a few years) an increase in births and deaths. Again, the effects are modest. The patterns contained in Figure 6 are a bit different. Here an increase in firm deaths has essentially no effect on productivity, and depresses birth rates, but raises future death rates. The latter effect is familiar from our analysis of state data.

6. Summary

Our approach has been to examine the dynamic linkages among firm birth rates, death rates, and productivity using panel data at the state and industry level. Using the state-level data, we find that shocks to productivity are quite persistent. Thus, to the extent that state-level policies directly raise labor productivity, these effects will be long lasting.

In addition, the data reveal that increases in the birth rate of firms leads, after some lag, to higher levels of productivity. This empirical relationship is at the heart of the notion of Schumpeterian creative destruction. There is now considerable evidence that government policies that improve access to capital (Holtz-Eakin, Joulfaian, Rosen 1994a, 1994b) or reduce tax rates (Bruce 1999; Gentry and Hubbard 2000) raise the rate of entry of new entrepreneurs. Our findings link these policies to enhanced productivity. An important caveat to this finding, however, is the fact that higher death rates do not seem to be related to productivity growth, a finding at odds with the simple version of Schumpeterian creative destruction.

Endnotes

1. See http://www.bea.doc.gov/bea/regional/gsp/.

2. We thank Sandra Black and Phil Strahan for generously providing these data.

3. See http://www.sba.gov/advo/stats/.

4. Preliminary analysis indicated that each variable was well-described by an AR(1) and no series contained a significant second-order, AR(2), component.

5. Notice that $\ln y_t = \rho \ln y_{t-1}$ may be re-written as $\ln y_t - \ln y_{t-1} = (\rho - 1)\ln y_{t-1}$.

6. The sole exception being the state of Washington.

7. As with the univariate estimates, some preliminary investigation indicated that a single lag of each variable was sufficient to capture the dynamics.

8. We focus on the logarthmic specification in what follows. Estimates of the corresponding levels equations are available from the authors.

9. In the table we report two different estimates of the standard error of each coefficient. The top estimate uses the robust covariance matrix e.g., Andrews (1991) with a Parzen kernel. The bottom estimate is derived from the conventional covariance matrix.

10. In constructing Figure 1, we do *not* employ an information regarding the contemporaneous covariances among productivity, births, and deaths. To do so requires placing a causal structure on these relationships. Our interest is on the subsequent dynamics.

11. As with the states, preliminary analysis indicated that each variable was well-described by an AR(1).

12. As before, we do *not* employ an information regarding the contemporaneous covariances among productivity, births, and deaths.

Table 1. Summary Statistics: State-Level Data

State	Average Employment	Average Productivity	Birth Rate	Death Rate
Alabama	1741349	44.1	0.126	0.107
Alaska	263891	76.3	0.140	0.114
Arizona	1807410	45.8	0.153	0.126
Arkansas	1068520	41.9	0.127	0.107
California	14372250	57.0	0.132	0.125
Colorado	1937090	45.8	0.149	0.115
Connecticut	1724385	62.9	0.104	0.106
Delaware	367875	66.2	0.137	0.109
District of Columbia	463304	63.7	0.111	0.105
Florida	6159118	47.1	0.152	0.133
Georgia	3297656	50.2	0.141	0.117
Hawaii	560327	53.4	0.115	0.107
Idaho	497091	41.8	0.144	0.106
Illinois	5714791	54.6	0.113	0.098
Indiana	2786491	45.5	0.112	0.094
Iowa	1375721	45.2	0.099	0.086
Kansas	1217787	45.2	0.114	0.101
Kentucky	1601663	46.5	0.117	0.101
Louisiana	1708403	57.6	0.119	0.102
Maine	592957	40.1	0.117	0.110
Maryland	2236019	51.0	0.123	0.109
Massachusetts	3227209	54.3	0.108	0.105
Michigan	4282873	50.7	0.113	0.097
Minnesota	2432644	47.0	0.116	0.093
Mississippi	1015731	42.5	0.123	0.107
Missouri	2578472	46.1	0.119	0.105
Montana	375357	38.1	0.126	0.102
Nebraska	827084	44.6	0.104	0.091
Nevada	788827	51.4	0.174	0.131
New Hampshire	589702	47.4	0.122	0.116
New Jersey	3710342	64.5	0.119	0.111
New Mexico	645110	48.2	0.138	0.116
New York	8146869	65.7	0.116	0.112
North Carolina	3452835	46.1	0.124	0.101
North Dakota	295473	41.4	0.098	0.089
Ohio	5282098	48.0	0.104	0.092
Oklahoma	1360198	42.6	0.125	0.108
Oregon	1477408	46.0	0.135	0.110
Pennsylvania	5570695	49.7	0.100	0.093
Rhode Island	467786	48.1	0.109	0.108
South Carolina	1601018	43.3	0.130	0.108
South Dakota	345718	44.1	0.112	0.092
Tennessee	2524394	44.8	0.124	0.105
Texas	8322322	52.8	0.137	0.117
Utah	896083	40.9	0.152	0.112
Vermont	301714	40.4	0.110	0.102
Virginia	2989839	49.5	0.124	0.106
Washington	2484644	51.6	0.143	0.116
West Virginia	653952	45.3	0.111	0.098
Wisconsin	2545284	44.9	0.104	0.087
Wyoming	221088	61.2	0.127	0.104

Table 2. Ordinary Least Squared Estimate of an AR(1) Model)

State	Productivity		Birth		Death	
	Level	ln	Level	ln	Level	ln
Alabama	0.951	0.931	-0.621	-0.636	0.438	0.432
	(3.920)[a]	(3.892)	(-1.309)	(-1.353)	(1.119)	(1.098)
Alaska	0.318	0.352	0.056	0.062	0.300	0.302
	(2.338)	(2.356)	(0.127)	(0.139)	(1.216)	(1.174)
Arizona	0.966	0.939	-0.697	-0.673	0.462	0.465
	(6.104)	(5.831)	(-0.864)	(-0.899)	(1.611)	(1.581)
Arkansas	0.879	0.861	-0.624	-0.638	0.451	0.450
	(4.685)	(4.696)	(-1.429)	(-1.470)	(0.898)	(0.906)
California	1.610	1.568	0.187	0.182	0.427	0.421
	(2.206)	(2.171)	(0.405)	(0.396)	(1.082)	(1.063)
Colorado	1.233	1.199	-0.620	-0.592	0.310	0.319
	(6.334)	(6.295)	(-1.148)	(-1.138)	(0.758)	(0.779)
Connecticut	1.230	1.198	-0.781	-0.770	0.671	0.667
	(5.934)	(5.924)	(-1.600)	(-1.617)	(2.316)	(2.306)
Delaware	0.493	0.476	-0.145	-0.150	0.286	0.295
	(1.872)	(1.838)	(-0.293)	(-0.306)	(0.672)	(0.692)
Florida	0.835	0.921	0.056	0.070	0.515	0.514
	(4.744)	(4.724)	(0.124)	(0.155)	(1.373)	(1.370)
Georgia	1.018	0.986	-0.338	-0.336	0.496	0.488
	(6.737)	(6.648)	(-0.599)	(-0.600)	(1.332)	(1.304)
Hawaii	0.419	0.427	0.566	0.557	0.258	0.255
	(1.482)	(1.506)	(1.712)	(1.668)	(0.499)	(0.500)
Idaho	0.847	0.845	-0.899	-0.888	1.582	1.453
	(3.696)	(3.712)	(-2.106)	(-2.170)	(2.207)	(2.120)
Illinois	1.083	1.059	-0.307	-0.297	0.267	0.277
	(5.017)	(4.977)	(-0.577)	(-0.562)	(0.483)	(0.506)
Indiana	1.013	0.992	-0.490	-0.488	0.396	0.401
	(4.852)	(4.742)	(-0.975)	(-0.978)	(0.724)	(0.746)
Iowa	1.030	1.004	-0.357	-0.358	-0.535	-0.527
	(2.717)	(2.654)	(-0.703)	(-0.706)	(-0.720)	](-0.725)
Kansas	0.404	0.387	-0.436	-0.440	0.473	0.463
	(0.450)	(0.437)	(-0.780)	(-0.801)	(1.461)	(1.399)
Kentucky	1.089	1.072	-0.055	-0.028	0.578	0.578
	(7.082)	(6.968)	(-0.093)	(-0.048)	(1.760)	(1.754)

Table 2. Continued

State	Productivity		Birth		Death	
	Level	ln	Level	ln	Level	ln
Louisiana	0.442	0.440	-0.201	-0.198	0.276	0.261
	(1.123)	(1.116)	(-0.379)	(-0.372)	(0.821)	(0.754)
Maine	1.735	1.714	0.358	0.319	0.661	0.665
	(2.650)	(2.635)	(0.509)	(0.472)	(4.330)	(4.135)
Maryland	0.932	0.925	-0.423	-0.414	0.347	0.362
	(3.272)	(3.322)	(-0.879)	(-0.868)	(0.774)	(0.810)
Massachusetts	1.157	1.132	-0.330	-0.309	0.740	0.747
	(4.276)	(4.188)	(-0.506)	(-0.494)	(3.081)	(3.211)
Michigan	0.819	0.921	-0.298	-0.284	0.294	0.301
	(2.770)	(2.821)	(-0.585)	(-0.561)	(0.615)	(0.635)
Minnesota	1.280	1.234	-0.123	-0.109	0.288	0.290
	(2.504)	(2.431)	(-0.218)	(-0.195)	(0.669)	(0.672)
Mississippi	0.926	0.911	-0.027	-0.009	0.291	0.270
	(4.824)	(4.810)	(-0.041)	(-0.013)	(0.808)	(0.737)
Missouri	0.890	0.869	-0.547	-0.558	0.052	0.044
	(3.324)	(3.228)	(-1.265)	(-1.296)	(0.102)	(0.086)
Montana	0.796	0.798	-0.457	-0.453	0.438	0.420
	(2.552)	(2.575)	(-1.017)	(-1.016)	(0.789)	(0.760)
Nebraska	0.686	0.670	-0.247	-0.243	0.192	0.195
	(2.282)	(2.268)	(-0.468)	(-0.462)	(0.372)	(0.381)
Nevada	0.653	0.649	-0.612	-0.588	0.266	0.277
	(2.833)	(2.824)	(-0.764)	(-0.808)	(0.502)	(0.526)
New Hampshire	1.174	1.112	-0.425	-0.417	0.722	0.732
	(5.300)	(4.992)	(-0.901)	(-0.887)	(5.018)	(4.864)
New Jersey	0.966	0.939	-0.384	-0.380	0.459	0.454
	(10.266)	(10.233)	(-0.421)	(-0.440)	(1.187)	(1.174)
New Mexico	0.763	0.736	-0.324	-0.330	0.223	0.217
	(4.709)	(5.029)	(-0.646)	(-0.659)	(0.476)	(0.466)
New York	1.116	1.094	-0.109	-0.330	0.223	0.217
	(4.083)	(3.969)	(-0.124)	(-0.659)	(0.476)	(0.466)
North Carolina	1.116	1.092	-0.223	-0.204	0.588	0.593
	(5.868)	(5.894)	(-0.247)	(-0.248)	(1.690)	(1.716)
North Dakota	-0.647	-0.649	0.044	0.060	0.500	0.509
	(-2.015)	(-2.023)	(0.097)	(0.133)	(1.181)	(1.222)
Ohio	1.029	1.008	-0.536	-0.529	0.323	0.338
	(2.658)	(2.632)	(-0.952)	(-0.954)	(0.620)	(0.661)

Table 2. Continued

State	Productivity		Birth		Death	
	Level	ln	Level	ln	Level	ln
Oklahoma	0.323	0.320	-0.061	-0.046	0.128	0.131
	(0.425)	(0.425)	(-0.104)	(-0.078)	(0.329)	(0.332)
Oregon	1.244	1.216	-0.692	-0.683	0.470	0.468
	(5.254)	(5.296)	(-1.537)	(-1.540)	(1.183)	(1.179)
Pennsylvania	0.929	0.914	-0.061	-0.035	0.306	0.307
	(10.201)	(10.274)	(-0.107)	(-0.059)	(0.696)	(0.697)
Rhode Island	2.052	1.964	-0.324	-0.313	0.616	0.607
	(2.614)	(2.600)	(-0.597)	(-0.586)	(1.854)	(1.830)
South Carolina	0.898	0.885	0.148	0.171	0.491	0.488
	(8.759)	(8.985)	(0.216)	(0.260)	(1.293)	(1.283)
South Dakota	0.289	0.293	-0.289	-0.282	0.175	0.185
	(0.996)	(1.023)	(-0.577)	(-0.569)	(0.294)	(0.318)
Tennessee	0.730	0.713	-0.231	-0.215	0.514	0.512
	(4.750)	(4.843)	(-0.365)	(-0.344)	(1.391)	(1.382)
Texas	1.233	1.206	-0.205	-0.200	0.422	0.424
	(9.819)	(9.485)	(-0.390)	(-0.380)	(1.189)	(1.184)
Utah	1.244	1.214	0.089	0.085	-0.122	-0.107
	(4.472)	(4.417)	(0.166)	(0.170)	(-0.212)	(-0.188)
Vermont	-0.126	-0.124	-0.295	-0.271	0.676	0.669
	(-0.219)	(-0.218)	(-0.483)	(-0.458)	(2.936)	(0.826)
Virginia	1.143	1.124	-0.407	-0.395	0.527	0.534
	(18.518)	(18.797)	(-0.845)	(-0.826)	(1.404)	(1.432)
Washington	0.831	0.816	-0.053	-0.034	1.281	1.207
	(1.994)	(2.001)	(-0.104)	(-0.067)	(1.813)	(1.757)
West Virginia	0.887	0.882	-0.279	-0.266	0.523	0.520
	(5.343)	(5.320)	(-0.492)	(-0.477)	(1.623)	(1.590)
Wisconsin	1.156	1.132	0.002	0.024	0.104	0.107
	(5.004)	(4.904)	(0.004)	(0.041)	(0.186)	(0.192)
Wyoming	0.712	0.700	0.120	0.122	0.035	0.062
	(1.603)	(1.572)	(0.328)	(0.340)	(0.051)	(0.093)

[a]Numbers in parentheses are t-statistics.
*with time dummy and state dummy. Others without time dummy.
Source:

Table 3. HNR-GMM Estimates

Dependent Variable	Independent Variable: Lagged Productivity	Lagged Birth	Lagged Death
ln(productivity)	0.008		
	(2.666)		
	0.025	0.003	0.012
	(4.028)	(1.748)	(4.838)
ln(birth)		0.102	
		(4.985)	
	-0.004	0.144	0.094
	(-0.167)	(19.633)	(13.154)
ln(death)			0.143
			(14.016)
	0.244	0.098	0.168
	(8.670)	(17.551)	(18.447)

( ): t-ratio. All with time dummy
Source:

Table 4. Within-Group Estimates

Dependent Variable	Independent Variable		
	Lagged Productivity	Lagged Birth	Lagged Death
ln(productivity)	0.83081707		
	(0.20549712)[a]		
	[0.03156333][b]		
	0.74317996	-0.037517889	-0.090426189
	(0.21441361)	(0.07341662)	(0.07744455)
	[0.03305527]	[0.01721960]	[0.01690622]
ln(birth)		-0.17170939	
		(0.33679881)	
		[0.06501906]	
	0.35800526	-0.20297937	0.1510311
	(0.57079632)	(0.37472571)	(0.29888429)
	[0.13010549]	[0.06777632]	[0.06654283]
ln(death)			0.51694431
			(0.23237391)
			[0.04445074]
	0.00069016	-0.26193602	0.58995199
	(0.43364879)	(0.2558421)	(0.22593814)
	[0.09746676]	[0.05077371]	[0.04984966]

[a]Numbers in parentheses are standard errors.

[b]Standard errors were computed using robust covariance matrix with a parzen kermel and bandwith parameter = 2.

Source:

Table 5. Summary Statistics

Industry	Employment	Average Productivity	Birth Rate	Death Rate
Agriculture	3,862,000	70.8	14.0	10.4
Mining	2,541,600	135.9	10.5	11.7
Construction	31,526,300	39.4	15.8	13.0
Manufacturing	95,615,600	66.0	8.9	8.7
Transportation, Communications, Public Utilities	42,077,500	88.9	14.7	12.0
Wholesale Trade	47,710,200	71.2	10.5	9.7
Retail Trade	193,935,900	25.5	11.7	11.3
Finance, Insurance, Real Estate	86,977,800	124.6	13.3	10.9
Services	343,455,300	34.0	12.0	9.7

Table 6. Ordinary Least Squares of an AR(1)

Industry	Productivity Level	Productivity ln	Birth Level	Birth ln	Death Level	Death ln
Agriculture, forest, fish	0.436	0.455	0.094	0.092	0.779	0.787
	(1.105)	(1.172)	(0.407)	(0.366)	(2.987)	(3.101)
Mining	1.159	1.125	0.022	0.053	0.500	0.545
	(9.250)	(8.698)	(0.036)	(0.090)	(1.189)	(1.263)
Construction	-0.082	-0.082	0.049	0.046	0.812	0.851
	(-0.196)	(-0.195)	(0.119)	(0.101)	(2.501)	(2.738)
Manufacturing	1.107	1.081	0.359	0.377	0.684	0.685
	(11.096)	(10.743)	(2.243)	(2.258)	(2.189)	(2.208)
Transportation and utilities	0.891	0.869	-0.070	-0.081	0.461	0.458
	(9.151)	(9.013)	(-0.165)	(-0.194)	(0.946)	(0.949)
Wholesale trade	1.032	0.962	-0.125	-0.105	0.202	0.217
	(4.441)	(4.567)	(0.243)	(-0.204)	(0.444)	(0.477)
Retail trade	1.633	1.585	-0.429	-0.421	0.177	0.184
	(7.819)	(7.617)	(0.769)	(-0.763)	(0.357)	(0.373)
F.I.R.E.	0.499	0.494	-0.021	-0.022	0.202	-0.175
	(2.798)	(2.854)	(0.042)	(-0.044)	(-0.404)	(-0.350)
Services	0.290	0.295	-0.136	-0.110	0.228	0.236
	(1.626)	(1.636)	(-0.204)	(-0.169)	(0.384)	(0.405)
Polling	1.034	1.014	0.755	0.791	0.868	0.878
	(78.108)	(100.084)	(9.249)	(9.966)	(15.868)	(16.095)

Table 7. Within-Group Estimates

	Independent Variable		
Dependent Variable	Lagged Productivity	Lagged Birth	Lagged Death
ln(productivity)	0.93797351 (0.075498890)[a]		
	0.91820053 (0.080192723)	-0.055656560 (0.063446577)	-0.0059207031 (0.085345815)
ln(birth)		-0.027346294 (0.14826240)	
	-0.076433770 (0.20693033)	-0.0065635632 (0.16371836)	-0.13251264 (0.22022743)
ln(death)			0.50118081 (0.12914258)
	-0.15105833 (0.13320290)	-0.025876592 (0.10538697)	0.47358249 (0.14176236)

[a]Numbers in parentheses are standard errors. Standard errors were computed by assuming error-terms to be iid.

Source:

Figure 1
Effects of Productivity Shock

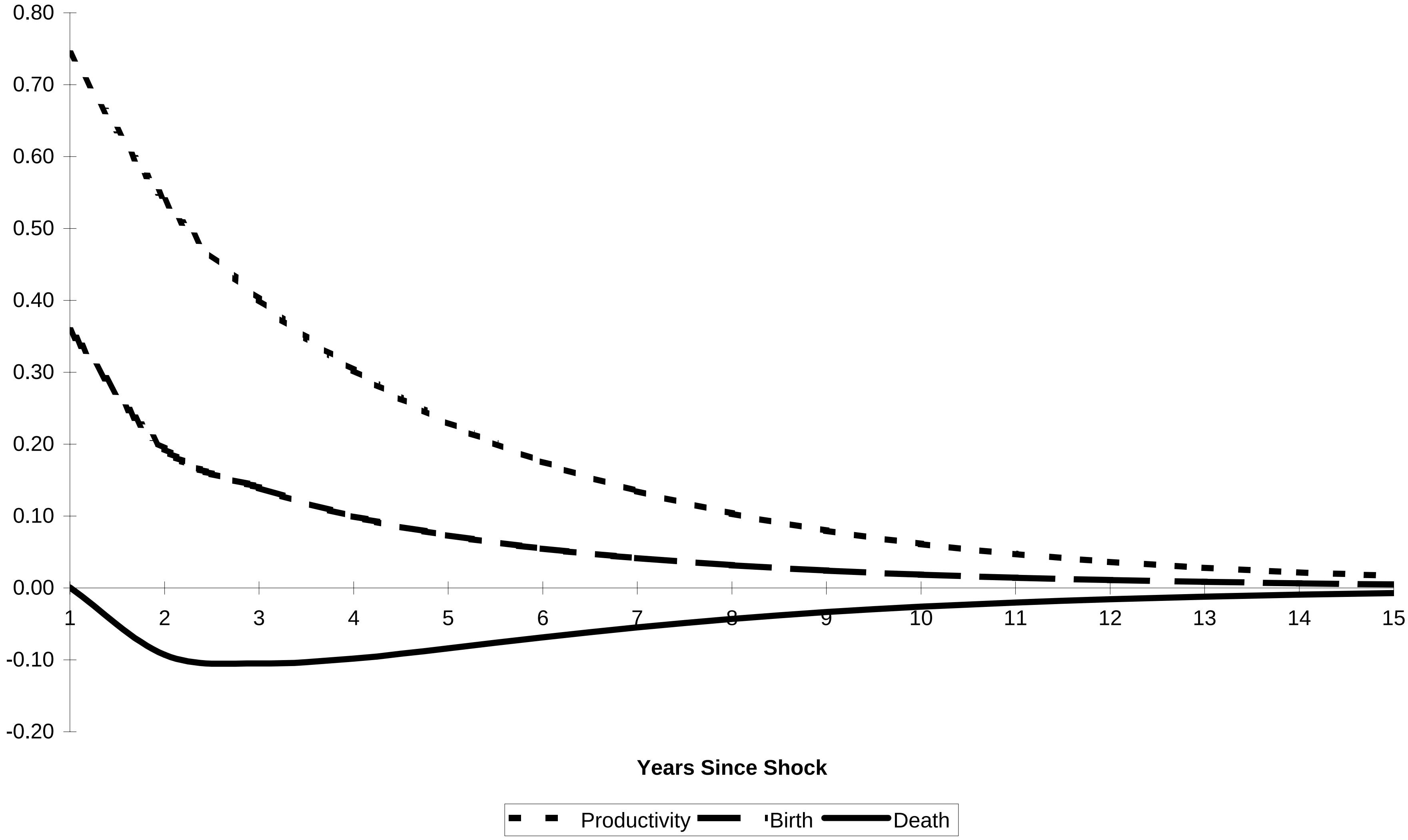


Figure 2
Effects of Birth Rate Shock

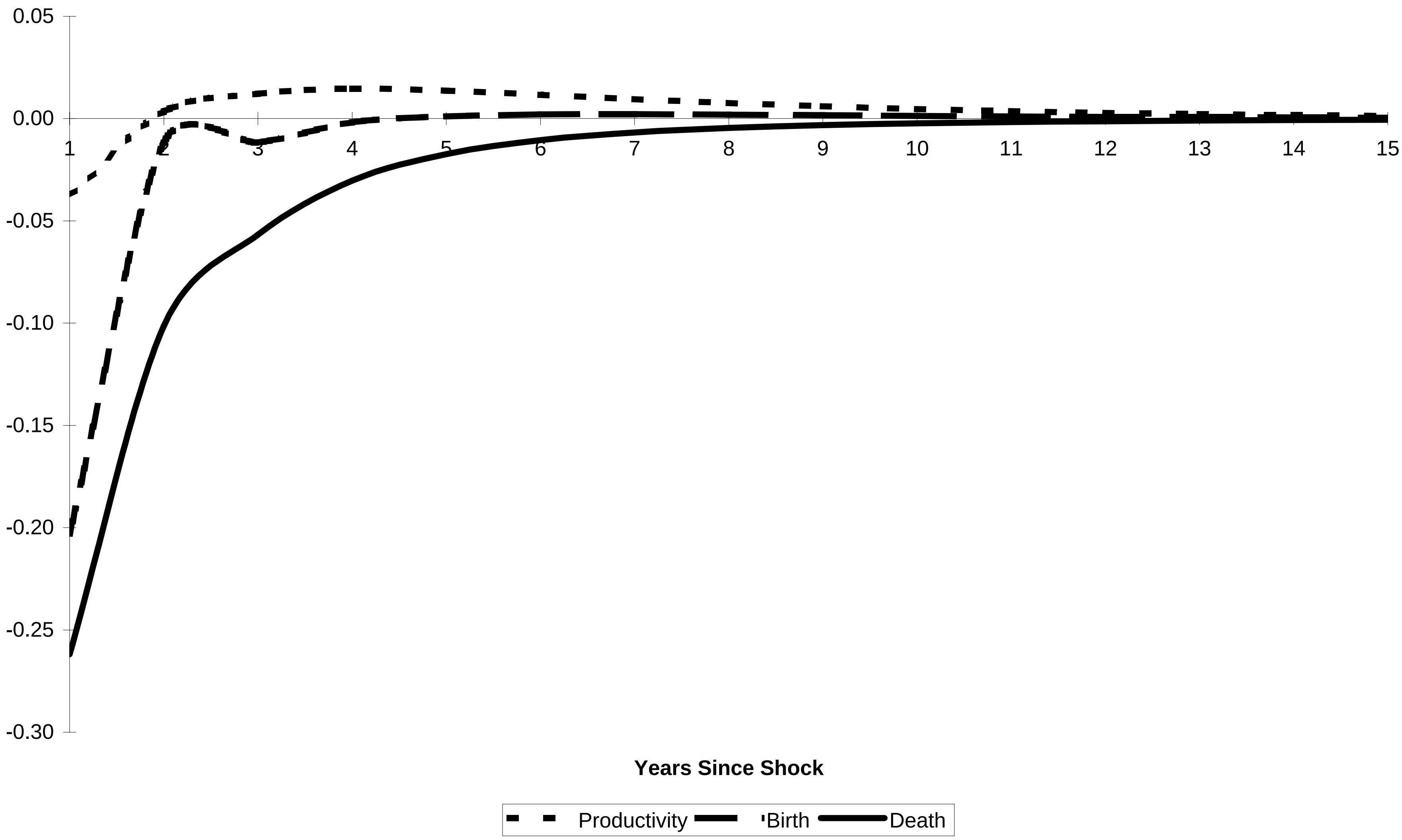


Figure 3
Effects of Death Rate Shock

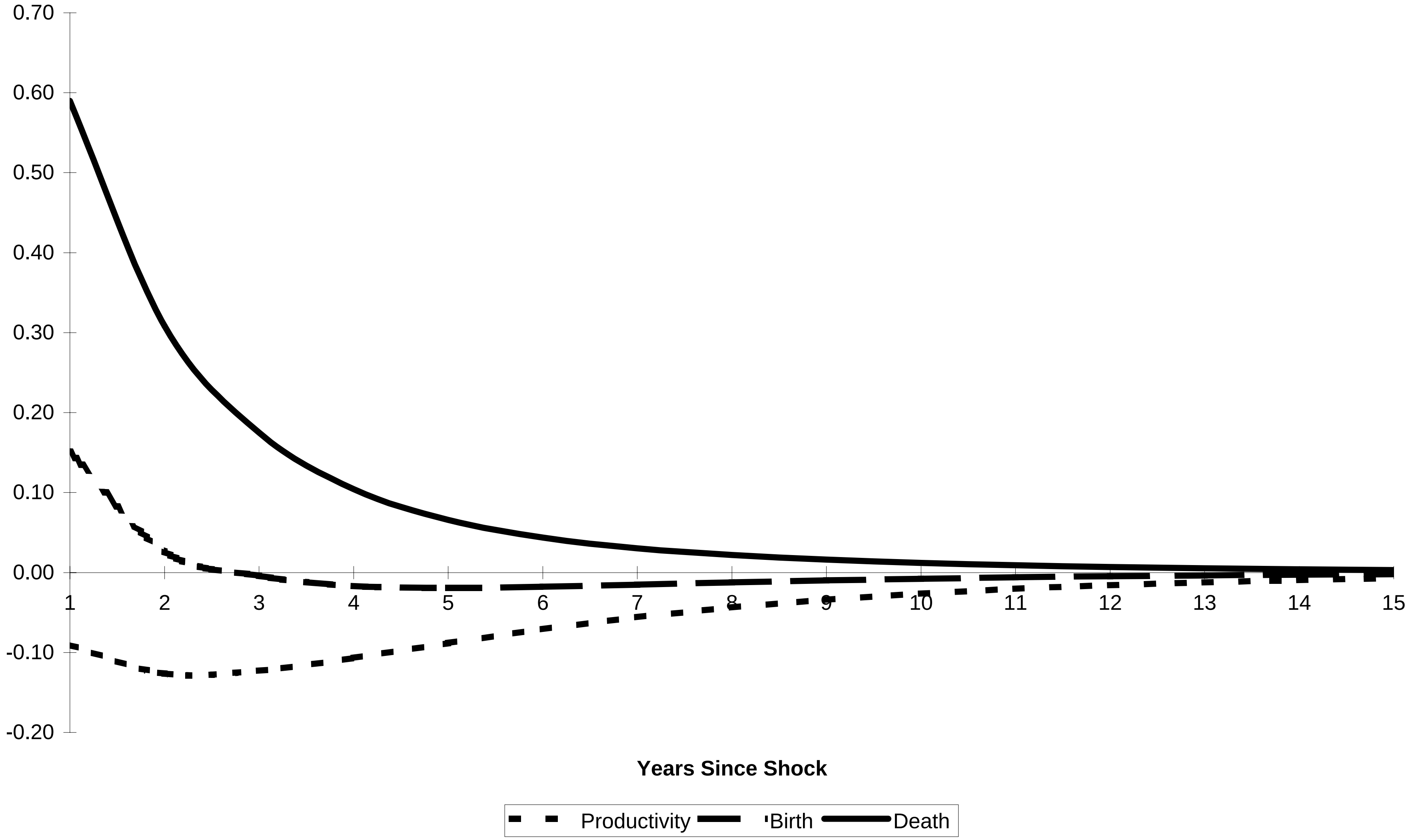


Figure 4
Effects of Productivity Shock

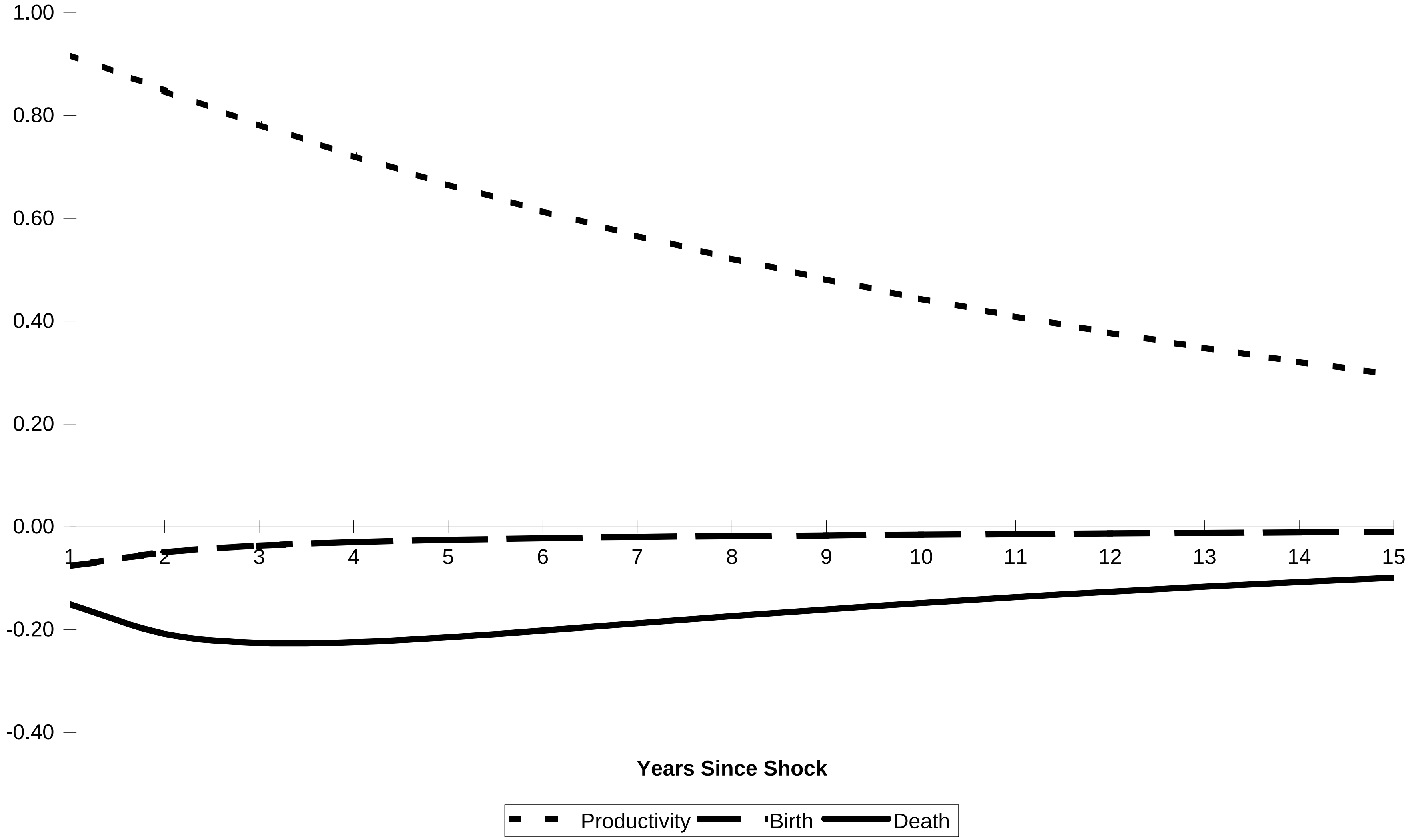


Figure 5
Effects of Birth Rate Shock

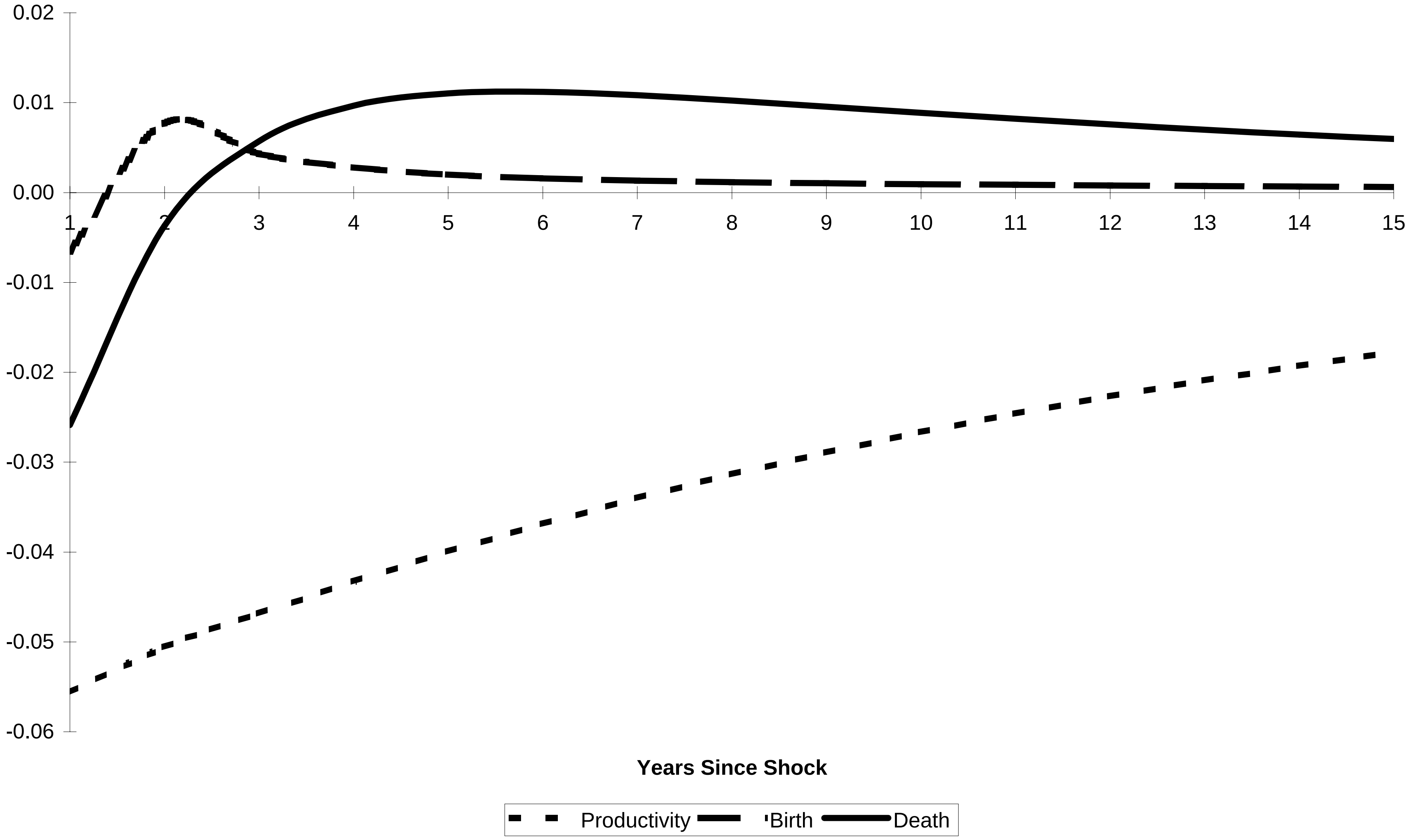
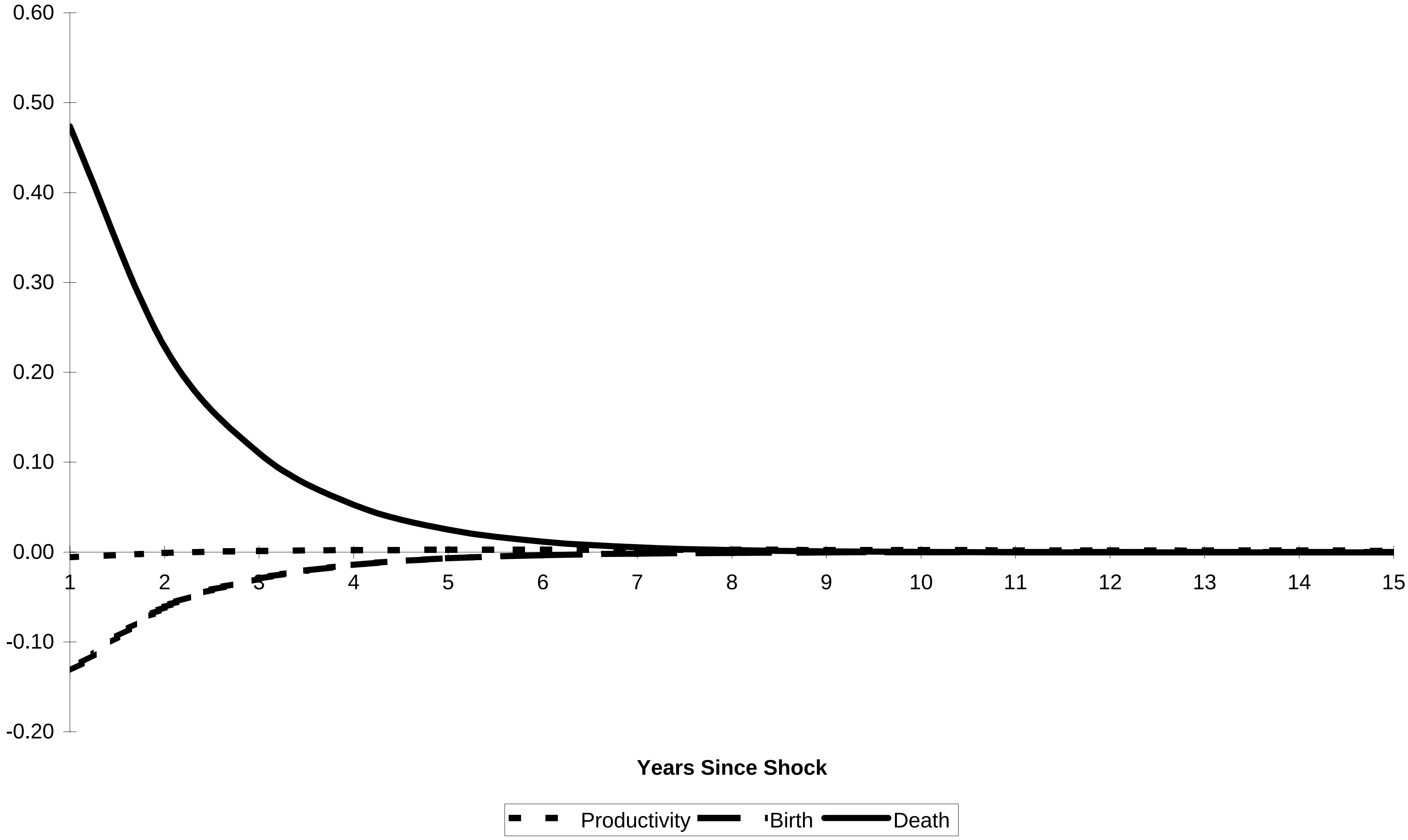


Figure 6
Effects of Death Rate Shock



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