

The Dynamic Relationship between Entrepreneurship, Unemployment, and Growth: Evidence from U.S. Industries

by

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The statements, findings, conclusions, and recommendations found in this study are those of the authors and do not necessarily reflect the views of the Office of Advocacy, the United States Small Business Administration, or the United States Government.

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Executive Summary

Our study looks at the dynamic relationship between entrepreneurship, unemployment, and growth across 10 sectors of the U.S. using quarterly data for the period 2000-2009. The models measure entrepreneurship using the net entry rate of establishments from the Business Employment Dynamics (BED) dataset compiled by the Bureau of Labor Statistics (BLS) and growth using real value added (GDP) from the Bureau of Economic Analysis (BEA). Past entrepreneurship has a *positive* effect on growth in 4 out of 10 sectors, and a *negative* effect on unemployment in 4 out of 10 sectors. Past growth has a *positive* effect on entrepreneurship in 4 out of 10 sectors, and a *negative* effect on unemployment in 6 out of 10 sectors. Past unemployment has a *positive* effect on entrepreneurship in 3 out of 10 sectors, and a *positive* effect on growth in 4 out of 10 sectors. In other words, entrepreneurship and growth have a dynamic relationship in which one generates the other; unemployment spurs entrepreneurship, but entrepreneurship dampens unemployment; and growth dampens unemployment, but unemployment spurs growth.

1. Introduction

Technological growth, entrepreneurship, and unemployment influence each other in numerous ways, forming a trio of inter-related components, yet the literature has traditionally emphasized the endogenous determination of one or two components of this trio, and the exogenous impact of one component on another, without taking into account the third. Consider the impact of entrepreneurship on growth. Endogenous growth theory suggests that entrepreneurship is an important determinant of growth. Such models predict or assume that an increase in the resources devoted toward innovation and R&D mechanically lead to higher growth, implying positive correlation between entrepreneurship and growth (Aghion and Howitt, 1992; Grossman and Helpman, 1991; Segerstrom, 1991, 1998; Romer, 1990; Jones, 1995); entrepreneurship is the means by which to launch, but not sustain, the economy, such that eventually it ceases altogether (Peretto, 1998, 1999a); and the growth rate and rate of entry may be positively or negatively correlated as the economy evolves over time (Peretto, 1999b). Next consider the impact of growth on unemployment. An increase in growth leads to a decrease in unemployment when technological change is disembodied (Pissarides, 1990); or an increase in unemployment when technological change is embodied (Aghion and Howitt, 1994). Finally, Fonseca et al. (2001) study the endogenous determination of entrepreneurship and unemployment, to find that the two are negatively related.

Rasteletti et al. (2010) argue that the three components of technological growth, entrepreneurship, and unemployment should not be studied in isolation or in pairs because doing so may engender a misleading over-simplification. In a model of search examining the impact of various forms of exogenous technical change on entrepreneurship and unemployment, they find that these important results in the literature concerning the impact of growth on unemployment no longer necessarily hold when one incorporates entrepreneurship; and the result concerning the

relationship between entrepreneurship and unemployment no longer necessarily holds when one incorporates growth. In a model embedding an occupational choice problem (such that the extent of entrepreneurship is endogenous) into an endogenous framework, Plehn-Dujowich and Li (2010) find that entrepreneurship has an inverted U relationship with growth.

This study empirically examines the interrelationship between entrepreneurship, unemployment, and growth in a dynamic context using vector autoregressions (VAR) with panel data across sectors of the U.S. economy. We test whether entrepreneurship and growth Granger-cause each other; unemployment and growth Granger-cause each other; and entrepreneurship and unemployment Granger-cause each other. To measure entrepreneurship, we utilize the net entry rate of establishments from the Business Employment Dynamics (BED) dataset compiled by the Bureau of Labor Statistics (BLS). The unemployment rate is measured at the sector level by the BLS. To measure growth, we utilize real GDP (specifically, value added) from the Bureau of Economic Analysis (BEA). Furthermore, we draw upon recent econometric advances in the estimation of dynamic models that exhibit cross-sectional dependence. Indeed, the recent financial crisis has demonstrated that macroeconomic shocks may affect large collections of U.S. industries. Traditional VAR methods do not allow for this possibility.

Our integrated sample consists of 10 sectors spanning quarterly data for 2000-2009. The following 10 sectors are examined due to the constraints of the unemployment dataset from the BLS: Construction (NAICS 23), Manufacturing (NAICS 31-33), Wholesale and retail trade (NAICS 42, 44-45), Transportation and utilities (NAICS 22, 48-49), Information (NAICS 51), Financial activities (NAICS 52-53), Professional and business services (NAICS 54-56), Educational and health services (NAICS 61-62), Leisure and hospitality (NAICS 71-72), and Other services (NAICS 81).

Past entrepreneurship has a *positive* Granger-causal effect on growth in 4 out of 10 sectors, and a *negative* Granger-causal effect on unemployment in 4 out of 10 sectors. Past growth has a *positive* Granger-causal effect on entrepreneurship in 4 out of 10 sectors, and a *negative* Granger-causal effect on unemployment in 6 out of 10 sectors. Past unemployment has a *positive* Granger-causal effect on entrepreneurship in 3 out of 10 sectors, and a *positive* Granger-causal effect on growth in 4 out of 10 sectors. This last result is surprising: one would not expect past unemployment to enhance growth. This may reflect the characteristics of the business cycle whereby periods of economic contractions are followed by periods of economic expansions.

The research infers the following about the dynamic Granger-causal relationships between entrepreneurship and growth, unemployment and entrepreneurship, and growth and unemployment. Entrepreneurship and growth have a dynamic relationship in which one generates the other: past entrepreneurship has a *positive* Granger-causal effect on growth in 4 out of 10 sectors, and past growth has a *positive* Granger-causal effect on entrepreneurship in 4 out of 10 sectors. Unemployment spurs entrepreneurship, but entrepreneurship dampens unemployment: past unemployment has a *positive* Granger-causal effect on entrepreneurship in 3 out of 10 sectors, but past entrepreneurship has a *negative* Granger-causal effect on unemployment in 4 out of 10 sectors. Growth dampens unemployment, but unemployment spurs growth: past growth has a *negative* Granger-causal effect on unemployment in 6 out of 10 sectors,

but past unemployment has a *positive* Granger-causal effect on growth in 4 out of 10 sectors.

This paper is organized as follows. We review the literature in Section 2; describe the datasets in Section 3; outline in Section 4 the econometric techniques; and discuss the empirical results in Section 5.

2. Literature Review

This section reviews the empirical literature examining the relationships between growth, entrepreneurship, and unemployment; and then review theories of entrepreneurship.

2.1 Empirical Studies Relating Growth and Entrepreneurship

In understanding the relationship between entrepreneurship and growth, the empirical literature has mostly focused on the impact of the former on the latter. In doing so, studies have conducted regional and country-level analyses considering employment, output, and productivity growth. Entrepreneurship is a multidimensional concept that is hard to measure precisely; the wide range of results reflects this complexity. The following is a review of empirical studies using the most prevalent measures of entrepreneurial activity: the self-employment rate, new business startups, and measures developed by the Global Entrepreneurship Monitor (GEM) and the World Bank Group Entrepreneurship Survey (WBGES).

2.1.1 Self-Employment as Entrepreneurship

The evidence is mixed as it pertains to the relationship between self-employment and economic growth. In Folster (2000), self-employment has a positive impact on overall employment in 24 Swedish counties from 1976 to 1995; and self-employment Granger-causes employment, but employment does not Granger-cause self-employment. By contrast, Blanchflower (2000) finds that the annual change in the self-employment rate has a negative effect on real GDP growth in OECD countries for the period 1966-1996; and using a variety of specifications and econometric techniques, Salgado-Banda (2007) finds that self-employment is negatively correlated with real GDP per capita growth in 22 OECD countries over the period 1980-1995.

In a 1976-1996 study of 23 OECD countries, Carree et al. (2002) investigate whether a country that deviates from its "equilibrium" business ownership rate suffers in terms of economic growth. The equilibrium rate is estimated as a function of the log of GDP per capita and its square; this relationship is found to be L-shaped or U-shaped, suggesting poorer countries have a higher self-employment rate. The authors then run a regression of the growth rate of GDP per capita against the absolute deviation of the business ownership rate from its equilibrium rate, as well as the initial GDP per capita (to control for the convergence effect). The coefficient on the deviation is estimated to be negative and significant, suggesting that too high or too low self-employment is detrimental to growth. However, most countries have a self-employment rate

below their corresponding equilibrium value (a notable exception being Italy); thus, most countries would experience a gain in growth in response to a rise in self-employment.

2.1.2 New Business Startups as Entrepreneurship

The majority of the evidence suggests new firm startups enhance growth. Audretsch and Keilbach (2004) introduce entrepreneurship capital into a standard production function, to find that the degree of entrepreneurship capital (measured by start-ups) has a positive impact on GDP across 327 West German regions in 1989-1992. Acs and Armington (2004) find that the birth rate of new firms has a positive effect on employment growth across 394 U.S. Labor Market Areas (LMAs) in the 1990s.

The impact of new business formation on growth has also been shown to depend on the period being examined, often requiring a number of years to take effect. Audretsch and Fritsch (2002) find that in 74 West German regions, new firm start-up rates have no significant impact on employment growth in the 1980s, but have a positive effect in the 1990s. In a 1980-1998 study of 60 British regions, van Stel and Storey (2004) obtain similar results. In a 1986-1989 study of the 75 planning regions of West Germany, Fritsch (1997) finds that new firm formation has a positive effect on employment change in the year when the new businesses are set up, but the effect is negative in subsequent periods. Examining West German regions, Audretsch and Fritsch (2003) find that the startup rate in the 1980s has no effect on employment growth in the 1980s, but a positive effect on employment growth in the 1990s. In a 1983-2002 study of 326 West German districts, Fritsch and Mueller (2004) find that, depending on the lag structure, new business formation may have a positive or negative impact on employment change.

A special issue of *Small Business Economics* (2008, Vol. 30, No. 1) is devoted to examining the impact of new business formation on subsequent regional employment, finding the effect to be positive in the short and long run, but negative in the medium run.¹ Acs and Mueller (2008) find a 6-year lag in the impact of new business formation on employment change in 320 U.S. Metropolitan Statistical Areas (MSA) during 1989-2003. The lag structure is S-shaped, U-shaped, or monotonically decreasing depending on the type of entry and the characteristics of the region. Arauzo-Carod et al. (2008) find a 7-year lag, S-shaped pattern in Spanish manufacturing sectors during 1978-1996. Baptista et al. (2008) find a 10-year lag, U-shaped pattern in 30 Portuguese regions during 1982-2002. Fritsch and Mueller (2008) find a 10-year lag, S-shaped pattern in 74 planning regions of West Germany during 1983-2002 that differs across regions according to population density and GDP per worker. Mueller et al. (2008) find an 8-year lag, S-shaped pattern in 60 U.K. regions during 1980-2003 with a positive (negative) effect in high-enterprise (low-enterprise, respectively) counties. van Stel and Suddle (2008) find an 8-year lag across 40 regions and 5 sectors in the Netherlands during 1988-2002 with a pattern whose shape varies depending on the time period and sector. In a 1972-2002 study of 21 OECD countries, Carree and Thurik (2008) find a 14-year lag, S-shaped pattern.

¹ Fritsch (2008) provides an overview and introduction.

2.1.3 The Global Entrepreneurship Monitor (GEM) and World Bank Group Entrepreneurship Survey (WBGES)

The Global Entrepreneurship Monitor (GEM) research program developed a variety of country-level measures of entrepreneurial activity, including Total Entrepreneurial Activity (TEA) and nascent entrepreneurship (Reynolds et al., 2005).² Findings based on GEM suggest the relationship between entrepreneurship and growth is non linear. Using GEM 2002 data spanning 36 countries, Wennekers et al. (2005) find a U-shaped relationship between nascent entrepreneurship and the level of economic development measured either by per capita income or an index of innovative capacity. The authors obtain similar findings using TEA. Examining 37 countries, Wong et al. (2005) assess the influence on growth in GDP per employee of four types of entrepreneurship: TEA, opportunity TEA, necessity TEA, and high growth potential TEA.³ The authors find that only high growth potential entrepreneurship has a significant positive impact on economic growth. Van Stel et al. (2005) find that TEA influences GDP growth in a sample of 36 countries, but this effect depends on the level of income per capita: TEA has a negative (positive) effect on GDP growth in poorer (richer, respectively) countries.

AcS et al. (2008) compare GEM, which measures early stage entrepreneurial activity, with the World Bank Group Entrepreneurship Survey (WBGES), which measures formal business registration. The authors calculate the spread between "nascent" entrepreneurship in GEM (the percentage of adults aged 18-64 who are setting up a business) and "corporate" entrepreneurship in the WBGES (the number of newly registered limited liability firms as a percentage of the adult population); and the spread between "baby" entrepreneurship in GEM (the percentage of adults aged 18-64 who are currently an owner-manager of a new business paying salaries for less than 42 months) and corporate entrepreneurship in WBGES. The authors find that entry tends to be higher in the WBGES compared to GEM in developed countries, while GEM tends to report higher levels of early stage entrepreneurship in developing countries compared to the WBGES business entry; and the differences are related to local regulatory barriers measured by four indicators of difficulties in starting, operating, and closing a business, and operational risks (including political, law and order, and economic risks), after controlling for the level of economic development. Their findings suggest that entrepreneurs in developed countries have greater ease and incentives to incorporate.

Klapper et al. (2008) use the WBGES to study the number of total and newly registered businesses across 84 countries spanning 2003 to 2005. The authors utilize three measures of entrepreneurship: business density, the entry rate, and entry per capita. Employing random-effects GLS and population-averaged Generalized Estimating Equations (GEE), the

² TEA is the percentage of adults aged 18-64 establishing a business or owning-managing a young firm. Nascent entrepreneurship is the percentage of adults aged 18-64 setting up a business.

³ Opportunity TEA is the percentage of adults aged 18-64 involved in TEA pursuing perceived opportunities. Necessity TEA is the percentage of adults aged 18-64 involved in TEA reflecting necessity (lack of alternatives). A venture is classified as having a "high growth potential" if it fulfills four criteria: (1) the venture plans to employ at least 20 employees in 5 years; (2) the venture indicates at least some market creation impact; (3) at least 15% of the customers of the venture normally live abroad; and (4) the technologies employed by the venture had not been widely available more than a year ago.

authors find a significant relationship between entrepreneurship and economic and financial development, governance, and the quality of the legal and regulatory environment. The authors also show that electronic registration procedures are important in the encouragement of greater business registration.

2.2 Empirical Studies Relating Growth and Unemployment

The correlation between unemployment and growth is ambiguous. Bean and Pissarides (1993) examine the correlation between unemployment and (labor and total factor) productivity growth for OECD countries over the period 1955-1985. The authors find weak evidence of a negative relationship between the two over the full sample, but no clear relationship within sub-periods. Caballero (1993) uses quarterly time series data from 1966:1 to 1989:4 for the U.S. and U.K., to find that the correlation between unemployment and per capita growth is unclear: at medium frequencies, it is positive for both countries; while at very low frequencies, it is positive for the U.K. and zero or even negative for the U.S. Results using labor productivity instead of per capita growth are similar. Bräuning and Pannenberg (2002) show that an increase in unemployment is associated with a decline in productivity growth in Europe and the U.S. during the period 1960-1997. Dell'Anno and Solomon (2008) find a negative correlation in the U.S. between quarterly changes in the unemployment rate and the quarterly growth rate of GDP between 1970 and 2004.

Most empirical research shows that productivity growth has a negative impact on unemployment. Based on a panel of 20 OECD countries spanning 1960-1996, Blanchard and Wolfers (2000) find that TFP growth has a negative effect on unemployment. Fitoussi et al. (2000) use data for 19 OECD countries over the period 1960-1998 to find that the Hodrick-Prescott-smoothed rate of change of labor productivity has a negative effect on unemployment. Using individual data in the U.K. spanning the period 1982-1999, Zagler (2006) finds that individual value added growth, measured by the GDP growth rate of the region and the sector in which the individual resides, has a negative impact on the individual unemployment rate, which captures the number of days a person spends being unemployed over the entire year. Using a panel of 15 industrialized countries covering the period 1965-1995, Pissarides and Vallanti (2007) find that TFP growth has a substantial negative impact on steady state unemployment, both in terms of the estimated elasticity and in terms of the contribution of TFP growth to the explanation of the change in the unemployment rate. Using historical time series for the U.K. from 1871 to 1999, Hatton (2007) finds that faster productivity growth reduces the non-accelerating inflation rate of unemployment (NAIRU) over the long run.

However, some studies find that the impact of growth on unemployment depends on the type of analysis being performed. Tripier (2006) describes the empirical co-movements of unemployment and labor productivity growth by means of spectral analysis over 1948-2000 for the U.S. The author finds that the co-movements are positive over the business cycle, but negative in the short and long run. Using a panel of 20 OECD countries spanning 1974 to 1989, Aghion and Howitt (1992) report an inverted-U impact of GDP growth on unemployment. The

results imply that countries with too fast or too slow growth rates have relatively lower unemployment rates, while countries with intermediate growth rates suffer the highest unemployment rates.

2.3 Theories of Entrepreneurship

Models of entrepreneurship are mostly labor market theories of occupational choice.⁴ In Khilstrom and Laffont (1979), individuals are heterogeneous in their risk preferences and choose between two occupations: entrepreneur or wage worker. In equilibrium, less risk-averse individuals become entrepreneurs. In Lazear (2005), individuals are endowed with two skills and choose between two occupations: a specialist that earns an income proportional to his maximum skill or an entrepreneur that earns an income proportional to his minimum skill. In equilibrium, individuals that do not excel in any one skill but are competent in both ("jack-of-all-trades") become entrepreneurs. In Evans and Jovanovic (1989), individuals are heterogeneous in their entrepreneurial ability and initial wealth, and choose between two occupations: entrepreneur or wage worker. In equilibrium, wealthy high-ability individuals become entrepreneurs. In Jovanovic (1994), individuals are heterogeneous in their managerial and labor skills, and choose between two occupations: a manager whose output depends on managerial skill, or a wage worker whose income depends on labor skill. In equilibrium, the sorting of individuals across occupations depends on the correlation between managerial and labor skills. In Lucas (1978), individuals are heterogeneous in their managerial ability and choose between two occupations, manager or wage worker (employed by a manager). In equilibrium, high-ability individuals become managers; and higher ability individuals operate firms with a larger workforce. Murphy et al. (1991), Oi (1983), and Rosen (1981) have similar results.

3. Data Sources

We merge datasets on unemployment, entrepreneurship, and growth.

3.1 Measure of Entrepreneurship

Our research draws from industry dynamics as our measure of entrepreneurship provided by the Business Employment Dynamics (BED) dataset compiled by the Bureau of Labor Statistics (BLS), which spans 3-digit industries over the period 1992-2009 on a quarterly basis. BED statistics are designed to track quarterly changes in the number of establishments and employment at the establishment level, revealing the dynamics underlying net changes in employment and establishments. These data include the number and rates of gross jobs gained at opening and expanding establishments, as well as the number and rates of gross jobs lost by closing and contracting establishments. BED statistics thereby measure the net change in employment at the establishment level that arises in one of four ways. A net increase in

⁴ See Parker (2004, pp. 43-65) for a detailed discussion of theories of entrepreneurship.

employment can come from either opening establishments or expanding establishments, which is the focus of this paper. A net decrease in employment can come from either closing establishments or contracting establishments. Gross job gains include the sum of all jobs added at either opening or expanding establishments. Gross job losses include the sum of all jobs lost in either closing or contracting establishments. The net change in employment is the difference between gross job gains and gross job losses.

Because our intent is to track entrepreneurship, as opposed to employment expansions and contractions, we solely draw from establishment entry and exit numbers. Specifically, we construct a popular measure of entrepreneurship based on industry dynamics, defined as follows. Let N_t denote the total number of establishments at time t , $E_{t,t+1}$ denote the number of establishments that entered between time t and time $t+1$, and $X_{t,t+1}$ denote the number of establishments that exited between time t and time $t+1$. The measure of entrepreneurship is the rate of net entry $(E_{t,t+1} - X_{t,t+1})/N_t$.

3.2 Measure of Unemployment

The Current Population Survey (CPS) from the Bureau of Labor Statistics (BLS) is used to infer the unemployment rate at the sector level, covering the period 2000-2011 on a monthly basis. To construct these sector-specific unemployment rates, the BLS assigns unemployed workers to the sector they used to work in before they became unemployed. Once unemployed workers have been assigned to each sector, the total number of unemployed workers and economically active workers per sector can be estimated. With this information, the BLS then constructs the sector-level unemployment rate.

The following 10 sectors are covered:

- Construction (NAICS 23).
- Manufacturing (NAICS 31-33).
- Wholesale and retail trade (NAICS 42, 44-45).
- Transportation and utilities (NAICS 22, 48-49).
- Information (NAICS 51).
- Financial activities (NAICS 52-53), which includes finance and insurance; and real estate rental and leasing.
- Professional and business services (NAICS 54-56), which includes professional, scientific and technical services; management of companies and enterprises; and administrative & support and waste management & remediation services.
- Educational and health services (NAICS 61-62).
- Leisure and hospitality (NAICS 71-72), which includes arts, entertainment, and recreation; and accommodation and food services.
- Other services (NAICS 81), except public administration.

It is possible to construct unemployment rates at more detailed industry levels using micro-data from IPUMS-CPS implementing the same methodology but at a micro level. However, because occupational skills are transferrable to some degree across 6-digit industries within the same sector, the unemployment rate at the 6-digit level is not as meaningful, reflecting in part labor mobility, the transferability of skills, and economic conditions. For this reason, we chose instead to utilize sector-level measures of unemployment.

The BLS also provide unemployment rates for Agriculture (NAICS 11) and Mining (NAICS 21), but we do not include these in our analysis since these industries are significantly different from all others.

3.3 Measure of Growth

The models use the growth rate of real Gross Domestic Product (GDP) by industry from the Bureau of Economic Analysis (BEA). The industry classifications are approximately at the 2-digit level. Using NAICS industry classifications, industry GDP is available for 1998-2010 on an annual basis. The BEA is in the midst of evaluating the procedures by which to publish quarterly GDP statistics by industry, but that data is not yet available. Numerous metrics related to GDP are available at the industry level, including value added, gross output, and shipments. We use value added as our measure of economic progress since, from an accounting perspective, value added equals sales minus the costs of intermediate goods. By subtracting the cost of intermediate goods, one ensures that only economic value added is being measured, as opposed to total sales.

Because our measure of unemployment is at the sector level, we must aggregate the 2-digit growth rates up to slightly higher levels. Studies involving the aggregation of total factor productivity (TFP) provide guidance in this regard. Domar aggregation is the most popular method when aggregating TFP growth rates, which consists of the following:

$$\hat{T}_{t,t+1}^D = \sum_{i=1}^I \left(\sum_{j=1}^I (V_t^j + V_{t+1}^j) / 2 \right)^{-1} [(S_t^i + S_{t+1}^i) / 2] \hat{T}_{t,t+1}^i$$

where $\hat{T}_{t,t+1}^D$ is the Domar-weighted TFP growth rate of the sector, $\hat{T}_{t,t+1}^i$ is the TFP growth rate of detailed industry i , S_t^i is nominal industry sales of industry i , V_t^i is the nominal value added of industry i , and I is the total number of detailed industries. Two common variations of Domar aggregation are to use value added as the weights:

$$\hat{T}_{t,t+1}^V = \sum_{i=1}^I \left(\sum_{j=1}^I (V_t^j + V_{t+1}^j) / 2 \right)^{-1} [(V_t^i + V_{t+1}^i) / 2] \hat{T}_{t,t+1}^i ;$$

and industry sales as the weights:

$$\hat{T}_{t,t+1}^S = \sum_{i=1}^I \left(\sum_{j=1}^I (S_t^j + S_{t+1}^j) / 2 \right)^{-1} [(S_t^i + S_{t+1}^i) / 2] \hat{T}_{t,t+1}^i.$$

Following the Tornqvist indexing methodology, the average starting and ending values of industry sales and value added are typically used when calculating the weights. We modify this approach by using employment levels as the weights to aggregate GDP growth up to the sector levels defined by the unemployment dataset.

3.4 Merging the Datasets

In terms of entrepreneurship, the net entry rate from the BED at the BLS is available at the 3-digit level for 1992-2009 on a quarterly basis. In terms of unemployment, the unemployment rate from the BLS is available at the sector level for 2000-2011 on a monthly basis. In terms of growth, real GDP growth from the BEA is available at the 2-digit level for 1998-2010 on an annual basis.

The frequency of our data varies from being monthly, quarterly, and annual. We selected the midway frequency point of quarterly. The most aggregated data is that pertaining to unemployment from the BLS, for which the following 10 sectors are covered: Construction (NAICS 23), Manufacturing (NAICS 31-33), Wholesale and retail trade (NAICS 42, 44-45), Transportation and utilities (NAICS 22, 48-49), Information (NAICS 51), Financial activities (NAICS 52-53), Professional and business services (NAICS 54-56), Educational and health services (NAICS 61-62), Leisure and hospitality (NAICS 71-72), and Other services (NAICS 81). Thus, we use these sectors as our primary industry classifications.

Our research integrates these datasets to obtain quarterly figures for these 10 sectors for 2000-2009. The net entry rate is aggregated from the 3-digit level to the sector level (using establishment level numbers), the sectors being defined by the BLS unemployment dataset. The unemployment rate is converted from being monthly to quarterly by calculating averages across quarterly periods. The growth rate is converted from annual to quarterly by assuming a constant geometric quarterly growth rate throughout the year.

4. Econometric Techniques

Using panel vector autoregressions (VAR), our models investigate the interrelationship between entrepreneurship, unemployment, and growth in a dynamic context. Three equations are estimated: one each for entrepreneurship, growth, and unemployment. On the right-hand side (RHS) of each are lags of entrepreneurship, unemployment, and growth. The econometric model is the following:

$$(1) G_{i,t} = \alpha_0 + \sum_{l=1}^m \alpha_l G_{i,t-l} + \sum_{l=1}^m \delta_l E_{i,t-l} + \sum_{l=1}^m \phi_l U_{i,t-l} + v_{i,t}$$

$$(2)E_{i,t} = \beta_0 + \sum_{l=1}^m \beta_l E_{i,t-l} + \sum_{l=1}^m \theta_l G_{i,t-l} + \sum_{l=1}^m \lambda_l U_{i,t-l} + \varepsilon_{i,t}$$

$$(3)U_{i,t} = \mu_0 + \sum_{l=1}^m \mu_l U_{i,t-l} + \sum_{l=1}^m \tau_l E_{i,t-l} + \sum_{l=1}^m \vartheta_l G_{i,t-l} + v_{i,t}.$$

The equations use i to identify the industry and t for time. E, U and G refer to our measures of entrepreneurship, unemployment, and growth, respectively. In equations (1)-(3), $\alpha, \delta, \varphi, \beta, \theta, \lambda, \mu, \tau, \vartheta$ are parameters to be estimated, m is the lag length, and v_{it}, ε_{it} and v_{it} are error terms. Six hypotheses are tested: (1) past entrepreneurship helps predict current economic growth, i.e. entrepreneurship Granger-causes growth; (2) past growth helps predict current entrepreneurship, i.e. growth Granger-causes entrepreneurship; (3) past entrepreneurship helps predict current unemployment, i.e. entrepreneurship Granger-causes unemployment; (4) past unemployment helps predict current entrepreneurship, i.e. unemployment Granger-causes entrepreneurship; (5) past unemployment helps predict current growth, i.e. unemployment Granger-causes growth; and (6) past growth helps predict current unemployment, i.e. growth Granger-causes unemployment.

4.1 Estimation of Dynamic Panel Models

Our research assumes the regression equations (1)-(3) have two-way error components disturbances, i.e. $v_{i,t} = \gamma_i + \eta_t + \zeta_{i,t}, \varepsilon_{i,t} = \omega_i + \pi_t + o_{i,t}$ and $v_{i,t} = \rho_i + \psi_t + \kappa_{i,t}$, where γ_i, ω_i and ρ_i denote the unobservable individual effects reflecting the different characteristics of the industries; η_t, π_t and ψ_t denote the unobservable time-specific effects; $\zeta_{i,t}, o_{i,t}$ and $\kappa_{i,t}$ are stochastic disturbance terms that are assumed to be independent and identically distributed (i.i.d.) with mean zero and variances $\sigma_{\zeta}^2, \sigma_o^2$ and σ_{κ}^2 , respectively. Lagged dependent variables are included in the RHS of equations (1)-(3). To illustrate the implications, consider equation (1). Since $G_{i,t}$ is a function of γ_i , it follows that $G_{i,t-1}$ is also a function of γ_i . Therefore, $G_{i,t-1}$, which is a right-hand regressor in (1), is correlated with the error term. This renders the OLS estimator biased and inconsistent (Baltagi, 2005). For the fixed effects estimator, the within transformation eliminates γ_i , but $G_{i,t-1} - \overline{G_{i,t-1}}$, where $\overline{G_{i,t-1}} = \sum_{t=2}^T G_{i,t-1} / (T-1)$, is correlated with $\zeta_{i,t} - \overline{\zeta_{i,t}}$ because $\overline{\zeta_{i,t}}$ contains $\zeta_{i,t-1}$, which in turn is correlated with $G_{i,t-1}$. As a result, the fixed effects estimator is also biased, and its consistency depends on T being large

(Baltagi, 2005). A similar analysis applies to equations (2) and (3).

To rectify this problem, we use difference generalized method of moments (GMM) (Holtz-Eakin et al., 1988; Arellano and Bond, 1991) and system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998). In difference GMM estimation, the first step is to take the first difference of the regression equations in order to eliminate individual effects. In panels with gaps, an alternative transformation is forward orthogonal deviation, i.e. to subtract the average of all future available observations of a variable, in order to maximize the sample size. Taking the first difference, equations (1)-(3) become:

$$(4) \quad \Delta G_{it} = \sum_{l=1}^m \alpha_l \Delta G_{i,t-l} + \sum_{l=1}^m \delta_l \Delta E_{i,t-l} + \sum_{l=1}^m \varphi_l \Delta U_{i,t-l} + \Delta \eta_t + \Delta \zeta_{it};$$

$$(5) \quad \Delta E_{it} = \sum_{l=1}^m \beta_l \Delta E_{i,t-l} + \sum_{l=1}^m \theta_l \Delta G_{i,t-l} + \sum_{l=1}^m \lambda_l \Delta U_{i,t-l} + \Delta \pi_t + \Delta o_{it};$$

$$(6) \quad \Delta U_{it} = \sum_{l=1}^m \mu_l \Delta U_{i,t-l} + \sum_{l=1}^m \tau_l \Delta E_{i,t-l} + \sum_{l=1}^m \vartheta_l \Delta G_{i,t-l} + \Delta \psi_t + \Delta \kappa_{i,t}.$$

Consider equation (4). $\Delta G_{i,t-1}$, $\Delta E_{i,t-1}$, and $\Delta U_{i,t-1}$ are correlated with $\Delta \zeta_{i,t}$; thus, they are endogenous variables in the first-difference equations. GMM estimation is then applied to the transformed equations with the first difference of lagged dependent variables being instrumented by past levels of lagged dependent variables, and the first difference of lagged endogenous explanatory variables being instrumented by past levels of lagged endogenous explanatory variables. In equation (4), the instrumental variables available for the first difference $\Delta G_{i,t-1}$ are $(G_{i,t-2}, G_{i,t-3}, \dots, G_{i,1})$; instruments for $\Delta E_{i,t-1}$ are $(E_{i,t-2}, E_{i,t-3}, \dots, E_{i,1})$; and instruments for $\Delta U_{i,t-1}$ are $(U_{i,t-2}, U_{i,t-3}, \dots, U_{i,1})$. These instruments are not correlated with $\Delta \zeta_{i,t}$ as long as $\zeta_{i,t}$ are not serially correlated. A similar analysis applies to equations (5) and (6).

Bond et al. (2001) and Bond (2002) argue that difference GMM estimators may be subject to weak instrument and finite sample biases. To address these problems, they use a system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998).⁵ The system GMM estimator combines equations of the first differences instrumented by lagged levels, with equations in levels instrumented by lagged first differences. For example, in equation (1), an extra set of instruments for $G_{i,t-1}$ is $(G_{i,t-2} - G_{i,t-3}), (G_{i,t-3} - G_{i,t-4}) \dots (G_{i,T-1} - G_{i,T-2})$. Because

⁵ The system GMM estimator has an additional assumption compared to the difference GMM estimator. See Bond et al. (2001) for details.

this procedure uses extra information compared to the untransformed model, the system GMM estimator is more efficient than the first difference GMM estimator. Thus, our research uses the system GMM estimator as the main estimator and also report difference GMM estimation results for comparison purposes.

The consistency of the system GMM estimator crucially depends on the validity of the instrumental variables. We test the validity of the instruments by performing a Sargan-Hansen test of overidentifying restrictions. We also test the validity of the additional instruments in the levels equations. Because the set of instruments used for the difference GMM estimator is a subset of the set of instruments used in the system GMM estimator, the validity of the additional overidentifying restrictions can be tested by comparing the Sargan statistic for the system GMM estimator with the Sargan statistic for the difference GMM estimator. Another key assumption for the consistency of the system GMM estimator is of no serial correlation in the stochastic error terms, i.e., ζ_{it} , o_{it} and κ_{it} . If this assumption is correct, we expect the differenced residuals,

i.e. $\zeta_{i,t} - \zeta_{i,t-1}$, $o_{i,t} - o_{i,t-1}$, and $\kappa_{i,t} - \kappa_{i,t-1}$, to display significant negative first-order serial correlation and no second-order serial correlation. We present tests for first-order and second-order serial correlation for the estimated residuals in first differences.

In order to estimate equations (1)-(3), it is important to choose the correct lag length m . We use Holtz-Eakin et al. (1988) sequential tests. We begin by estimating the model with a relatively large lag length \tilde{m} . The sum of squared residuals (SSR) for this estimation (Qu) is compared with the SSR of the estimation using $\tilde{m} - 1$ lags (Qr). The difference $L = Qr - Qu$ follows a Chi-squared distribution. This procedure is repeated with successively shorter lags until the lag length can no longer be reduced.

4.2 Estimation under Cross-Sectional Dependence

Although difference GMM and system GMM estimators resolve problems associated with lagged dependent variables and endogenous regressors in dynamic panel models, these methods typically assume that the disturbances are cross-sectionally independent. However, given that industries are our unit of analysis, the error terms in equations (1)-(3) are likely to be correlated with one another due to the presence of macroeconomic factors that affect all industries. To address error cross-sectional dependence in panel VAR models, we use a new method developed by Huang (2008).

To implement the Huang method, we need to impose further structure to the error process. Our research assumes that the error terms v_{it} , ε_{it} and u_{it} in equations (1)-(3) are given by:

$$(7) \quad v_{it} = \lambda_i^G f_t + v_{it};$$

$$(8) \quad \varepsilon_{it} = \lambda_i^E f_t + e_{it};$$

$$(9) \quad v_{it} = \lambda_i^U f_t + u_{it},$$

where λ are vectors factor loadings, f_t is a vector of cross-sectional shocks, and v_{it}, e_{it} and u_{it} are error terms. This error structure is commonly used in the empirical real business cycle (RBC) literature in macroeconomics. We also assume that f_t, v_{it}, e_{it} and u_{it} are i.i.d.

The Huang method consists of three steps. In the first step, the cross-sectional dependence is ignored and an estimate of the residuals for each cross-sectional unit is obtained using ordinary least squares (OLS). In the second step, factor analysis is applied to the residuals from first-stage estimation to obtain the estimates of the factors. In the third and final step, the model is re-estimated using the factor augmented fully modified (FM) VAR, a method developed by Philips (1995).

To illustrate the Huang method, we stack the system of equations (1)-(3) and the equations (7)-(9) for the error terms, to re-express them as

$$(10) \quad y_{it} = Ay_{it-1} + z_{it};$$

$$(11) \quad z_{it} = \lambda_i f_t + w_{it},$$

where y_{it}, z_{it} and w_{it} are $3 \times m \times 1$ vectors. In the first step, a first-stage estimate of A is obtained via OLS. If the factor loadings f_t and the error term w_{it} are i.i.d., then OLS provides a first-stage consistent estimator of A . Once the estimate of A (\hat{A}) is obtained, it can be used together with the vector y_{it} to produce the estimated residuals (\hat{z}_{it}). In the second step, factor analysis is applied to \hat{z}_{it} to obtain the estimates of λ_i and f_t . This is done by replacing \hat{z}_{it} into the equation for the error term $z_{it} = \lambda_i f_t + w_{it}$. After this, the objective function for the factor analysis is created and minimized with respect to λ_i and f_t :

$$(12) \quad \min_{\lambda_i, f_t} V(k) = (mNT)^{-1} \sum_{i=1}^N \sum_{t=1}^T \sum_{p=1}^M (\hat{z}_{itp} - \lambda_{ip}' f_t)^2,$$

where N is the number of cross-sectional units (i.e. industries), T is the number of time periods, and m is the number of variables in the original VAR equation. The solution to this minimization problem is given by:

$$(13) \quad \hat{\lambda}_{ip}' = \left(\sum_{t=1}^T f_t f_t' \right)^{-1} \left(\sum_{t=1}^T f_t \hat{z}_{itp} \right);$$

$$(14) \hat{f}_t = \left(\sum_{i=1}^N \sum_{p=1}^m \lambda_{ip} \lambda'_{ip} \right)^{-1} \left(\sum_{i=1}^N \sum_{p=1}^m \hat{z}_{itp} \lambda_{ip} \right).$$

In the third step, fully modified VAR (FM-VAR) estimation is used. This method was originally developed by Phillips (1995) and it imposes no restrictions on the distributions of f_t and w_{it} . Let us assume that the optimal length estimated m equals q . Then our original VAR model can be re-written

$$(15) y_{it} = J_i(L)y_{it-1} + z_{it}; \text{ or}$$

$$(16) y_{it} = J_i^*(L)\Delta y_{it-1} + A_i y_{it-1} + z_{it},$$

$$\text{where } J_i(L) = \sum_{h=1}^q J_{ih} L^{h-1}, \quad J_i^*(L) = \sum_{h=1}^{q-1} J_{ih}^* L^{h-1}, \quad J_{ih}^*(L) = - \sum_{g=h+1}^q J_{ig} \quad \text{and } J_i = (J_{i1}^*, \dots, J_{i,q-1}^*).$$

To improve estimation, the estimated factors can be used. When these factors are included, the equation to be estimated becomes:

$$(17) y_{it} = J_i^*(L)\Delta y_{it-1} + A_i y_{it-1} + \lambda_i \hat{f}_t + w_{it}.$$

To obtain the estimators, we use an orthogonal transformation matrix $H_T = [\beta, \beta_\perp]$. Multiplying (17) by the orthogonal transformation matrix, we obtain the following:

$$(18) \tilde{y}_{1it} = \tilde{J}_1(L)\Delta y_{it-1} + \tilde{A}_{i11} \tilde{y}_{1it-1} + \tilde{\lambda}_{i11} \hat{f}_t + \tilde{w}_{1it};$$

$$(19) \tilde{y}_{2it} = \tilde{y}_{2it-1} + u_{2t};$$

$$(20) u_{2t} = \tilde{w}_{1it} + \tilde{J}_2(L)\Delta \tilde{y}_{it-1} + \tilde{A}_{i21} \tilde{y}_{it-1} + \tilde{\lambda}_{i21} \hat{f}_t,$$

where the coefficients $\tilde{J}_1, \tilde{J}_2, \tilde{A}_{i11}, \tilde{A}_{i21}, \tilde{\lambda}_{i11}$ and $\tilde{\lambda}_{i21}$ are elements of the partitioned matrices of $H_T' J_i H_T$, $H_T' A_i H_T$ and $H_T' \lambda_i H_T$. Tilted variables are left-multiplications of the original variables with H_T' . In matrix notation, equations (18)-(20) can be written as

$$(21) \underline{\tilde{y}}_1' = \tilde{F}_i \tilde{W}_i' + \tilde{w}_i',$$

where $\tilde{F}_i = (\tilde{J}_i, \tilde{A}_i, \tilde{\lambda}_i)$ and $\tilde{W}_i = (\Delta y_{it-1}, \tilde{y}_{1it-1}, \hat{f}_t)$.

Now to express the estimator:

$$(22) \quad \tilde{F}_i = [\underline{y}'_i \Delta y_i : \underline{y}'_i \underline{y}'_{i-1} - \tilde{\lambda}_i \tilde{\Omega}_{f \Delta \underline{y}'_i} \tilde{\Omega}_{\Delta \underline{y}'_i} (\Delta \underline{y}'_{i-1} \underline{y}_{i-1} - T \hat{\Delta}_{\Delta \underline{y}_{-1} \Delta \underline{y}_{-1}}) - \tilde{\Omega}_{e \Delta \underline{y}_{-1}} \tilde{\Omega}_{\Delta \underline{y}_{-1} \underline{y}_{-1}} (\Delta \underline{y}'_{i-1} \underline{y}_{i-1} - T \hat{\Delta}_{\Delta \underline{y}_{-1} \Delta \underline{y}_{-1}})] (W_i' W_i)^{-1}.$$

This estimator produces unbiased estimates. Huang's Monte Carlo simulations indicate that this procedure performs reasonably well when cross-sectional dependence is present.

5. Empirical Results

This section describes the properties of the sample and then the econometric results.

5.1 Descriptive Statistics

Figure 1 provides the net entry rate for 2000-2009 for each sector. There was a sharp drop in entrepreneurship in Information in 2000-2001 reflecting the tech crash, thereafter stabilizing, but exhibiting negative net entry throughout the entire sample period, suggesting the tech crash may have had a permanent effect on the extent of entrepreneurship in Information. Construction began experiencing a decrease in entrepreneurship in 2005, worsening up to 2009, reflecting the housing crisis, which interestingly thereby showed early warning signs in 2005. Educational and health services maintained a high level of entrepreneurship during the entire sample period and exhibited the most robust response to the financial crisis, suggesting long-run strength and growth potential in this sector.

Figure 2 provides the unemployment rate for 2000-2009 for each sector. The unemployment rate rose in all sectors beginning in 2007, reflecting the financial crisis. Construction is the sector that is the most sensitive to the business cycle, with Leisure and hospitality also being somewhat cyclical. Manufacturing also experienced a sharp rise in unemployment due to the crisis, rising approximately from 4% to 11%.

Figure 3 provides GDP growth for 2000-2009 for each sector. Growth has been erratic in all sectors, exhibiting significant volatility during the sample period, not entirely stemming from the business cycle. All sectors show strong drops due to the financial crisis, beginning in 2007. Construction began a sharp decline in growth starting in 2005, once again reflecting the early warning signs of the looming housing crisis. Information suffered a severe contraction during the tech crisis of 2000-2001 and has been highly volatile ever since.

5.2 Empirical Results

Our study has 3 systems of equations (one each for growth, entrepreneurship, and unemployment), and 10 sectors, yielding a total of 30 equations. In all cases, we find that the optimal lag length is close to or equal to one year (4 quarters), so we restrict the regressions to one year lag lengths for ease of exposition. This is partly due to the fact that we only have 9 years to work with. A longer time series might reveal greater lag lengths on average.

5.2.1 What Granger-Causes Entrepreneurship?

Table 1 provides the econometric results for the entrepreneurship equation. We find that both growth and unemployment generate entrepreneurship.

Past growth has a *positive* Granger-causal effect on entrepreneurship in the following 4 out of 10 sectors: Construction, Manufacturing, Wholesale and retail trade, and Information. In no sector do we find that past growth has a *negative* Granger-causal effect on entrepreneurship.

Past unemployment has a *positive* Granger-causal effect on entrepreneurship in the following 3 out of 10 sectors: Construction, Financial activities, and Professional and business services. In no sector do we find that past unemployment has a *negative* Granger-causal effect on entrepreneurship.

5.2.2 What Granger-Causes Unemployment?

Table 2 provides the econometric results for the unemployment equation. We find that both entrepreneurship and growth dampen unemployment.

Past entrepreneurship has a *negative* Granger-causal effect on unemployment in the following 4 out of 10 sectors: Construction, Transportation and utilities, Financial activities, and Professional and business services. In no sector do we find that past entrepreneurship has a *positive* Granger-causal effect on unemployment.

Past growth has a *negative* Granger-causal effect on unemployment in the following 6 out of 10 sectors: Construction, Manufacturing, Wholesale and retail trade, Professional and business services, Leisure and hospitality, and Other services. In no sector do we find that past growth has a *positive* Granger-causal effect on unemployment.

5.2.3 What Granger-Causes Growth?

Table 3 provides the econometric results for the growth equation. We find that both entrepreneurship and unemployment generate growth.

Past entrepreneurship has a *positive* Granger-causal effect on growth in the following 4 out of 10 sectors: Construction, Transportation and utilities, Financial activities, and Professional and business services. In no sector do we find that past entrepreneurship has a *negative* Granger-causal effect on growth.

Past unemployment has a *positive* Granger-causal effect on growth in the following 4 out of 10 sectors: Manufacturing, Wholesale and retail trade, Professional and business services, and Other services. This result may reflect the characteristics of the business cycle whereby periods of economic contractions are followed by periods of economic expansions. However, past unemployment has a *negative* Granger-causal effect on growth in Educational and health services.

5.2.4 What Do Entrepreneurship, Unemployment, and Growth Granger-Cause?

Another perspective on our findings is to examine what a change in entrepreneurship, growth, or unemployment lead to the subsequent year.

Past entrepreneurship has a *positive* Granger-causal effect on growth in 4 out of 10 sectors, and a *negative* Granger-causal effect on unemployment in 4 out of 10 sectors.

Past growth has a *positive* Granger-causal effect on entrepreneurship in 4 out of 10 sectors, and a *negative* Granger-causal effect on unemployment in 6 out of 10 sectors.

Past unemployment has a *positive* Granger-causal effect on entrepreneurship in 3 out of 10 sectors, and a *positive* Granger-causal effect on growth in 4 out of 10 sectors.

5.2.5 The Dynamic Granger-Causal Relationships between Entrepreneurship, Growth, and Unemployment

Finally, we examine the dynamic Granger-causal relationships between entrepreneurship and growth, unemployment and entrepreneurship, and growth and unemployment.

Entrepreneurship and growth have a dynamic relationship in which one generates the other: past entrepreneurship has a *positive* Granger-causal effect on growth in 4 out of 10 sectors, and past growth has a *positive* Granger-causal effect on entrepreneurship in 4 out of 10 sectors.

Unemployment spurs entrepreneurship, but entrepreneurship dampens unemployment: past unemployment has a *positive* Granger-causal effect on entrepreneurship in 3 out of 10 sectors, but past entrepreneurship has a *negative* Granger-causal effect on unemployment in 4 out of 10 sectors.

Growth dampens unemployment, but unemployment spurs growth: past growth has a *negative* Granger-causal effect on unemployment in 6 out of 10 sectors, but past unemployment has a *positive* Granger-causal effect on growth in 4 out of 10 sectors.

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Appendix A: Tables

Table 1: The Dynamic Determinants of the Net Entry Rate

	1-Year Lag Net Entry	1-Year Lag GDP Growth	1-Year Lag Unemployment	Constant	Pseudo R-squared
Construction (NAICS 23)	0.658** (0.274)	0.448* (0.227)	0.00123* (0.000632)	-0.0190** (0.00721)	0.617
Manufacturing (NAICS 31-33)	-0.0351 (0.237)	0.206** (0.0829)	0.000484 (0.000517)	-0.0122*** (0.00255)	0.251
Wholesale and retail trade (NAICS 42, 44-45)	-0.244 (0.185)	0.353*** (0.108)	0.000470 (0.000589)	-0.0120*** (0.00386)	0.360
Transportation and utilities (NAICS 22, 48-49)	0.595** (0.243)	0.0469 (0.0832)	0.000549 (0.000884)	-0.00610 (0.00405)	0.194
Information (NAICS 51)	0.151 (0.122)	0.201** (0.0794)	-0.000353 (0.000634)	-0.00777** (0.00323)	0.122
Financial activities (NAICS 52-53)	0.889*** (0.132)	0.290 (0.190)	0.00468*** (0.00165)	-0.0202*** (0.00717)	0.621
Professional and business services (NAICS 54-56)	0.576** (0.211)	0.236 (0.236)	0.00185* (0.00106)	-0.0176* (0.0103)	0.231
Educational and health services (NAICS 61-62)	0.0562 (0.179)	0.0322 (0.178)	-0.00111 (0.00102)	0.00479 (0.00335)	0.063
Leisure and hospitality (NAICS 71-72)	0.577*** (0.191)	0.00640 (0.0848)	-0.000262 (0.000484)	0.00120 (0.00449)	0.247
Other services (NAICS 81)	0.263 (0.248)	-0.00594 (0.0344)	-0.000232 (0.000427)	-0.000942 (0.00208)	0.050

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations

Table 2: The Dynamic Determinants of the Unemployment Rate

	1-Year Lag Net Entry	1-Year Lag GDP Growth	1-Year Lag Unemployment	Constant	Pseudo R-squared
Construction (NAICS 23)	-157.4*** (45.68)	-125.2** (47.50)	0.786*** (0.140)	4.011** (1.465)	0.852
Manufacturing (NAICS 31-33)	-95.29 (154.1)	-143.3*** (36.23)	0.190 (0.250)	5.241*** (1.180)	0.499
Wholesale and retail trade (NAICS 42, 44-45)	-69.07 (53.85)	-161.3*** (19.79)	0.320** (0.139)	5.192*** (0.870)	0.829
Transportation and utilities (NAICS 22, 48-49)	-258.1*** (65.96)	-10.88 (22.80)	0.270 (0.252)	2.876** (1.078)	0.493
Information (NAICS 51)	-71.49* (37.37)	-6.658 (23.62)	0.164 (0.195)	4.525*** (1.032)	0.137
Financial activities (NAICS 52-53)	-148.5*** (19.72)	5.821 (23.63)	0.798*** (0.238)	0.729 (1.041)	0.763
Professional and business services (NAICS 54-56)	-81.27* (46.00)	-228.6*** (45.69)	-0.415* (0.230)	13.28*** (2.079)	0.544
Educational and health services (NAICS 61-62)	-19.23 (58.82)	39.47 (41.32)	0.798** (0.319)	0.348 (0.989)	0.255
Leisure and hospitality (NAICS 71-72)	-54.45 (65.85)	-138.4*** (21.69)	0.328** (0.140)	7.404*** (1.181)	0.681
Other services (NAICS 81)	-157.2	-36.89**	0.514**	2.644**	0.316

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations

Table 3: The Dynamic Determinants of the GDP Growth Rate

	1-Year Lag Net Entry	1-Year Lag GDP Growth	1-Year Lag Unemployment	Constant	Pseudo R-squared
Construction (NAICS 23)	1.044*** (0.217)	0.720*** (0.216)	0.000972 (0.000632)	-0.00839 (0.00661)	0.795
Manufacturing (NAICS 31-33)	-0.499 (0.743)	0.649*** (0.155)	0.00541*** (0.00157)	-0.0317*** (0.00756)	0.503
Wholesale and retail trade (NAICS 42, 44-45)	-0.105 (0.631)	0.993*** (0.160)	0.00463*** (0.00109)	-0.0277*** (0.00727)	0.600
Transportation and utilities (NAICS 22, 48-49)	1.220*** (0.441)	-0.0873 (0.159)	0.00263 (0.00179)	0.00347 (0.00877)	0.190
Information (NAICS 51)	-0.375 (0.248)	-0.396*** (0.143)	0.000325 (0.00142)	0.0127** (0.00594)	0.127
Financial activities (NAICS 52-53)	0.443*** (0.107)	0.258 (0.180)	0.000429 (0.00132)	0.00771 (0.00562)	0.371
Professional and business services (NAICS 54-56)	0.564** (0.234)	1.104*** (0.239)	0.00491*** (0.000975)	-0.0367*** (0.00963)	0.443
Educational and health services (NAICS 61-62)	0.101 (0.203)	0.413*** (0.124)	-0.00223*** (0.000541)	0.0164*** (0.00221)	0.329
Leisure and hospitality (NAICS 71-72)	0.409 (0.634)	0.695*** (0.243)	0.00206 (0.00141)	-0.0157 (0.0123)	0.266
Other services (NAICS 81)	0.819	-0.479***	0.00356*	-0.00612	0.262

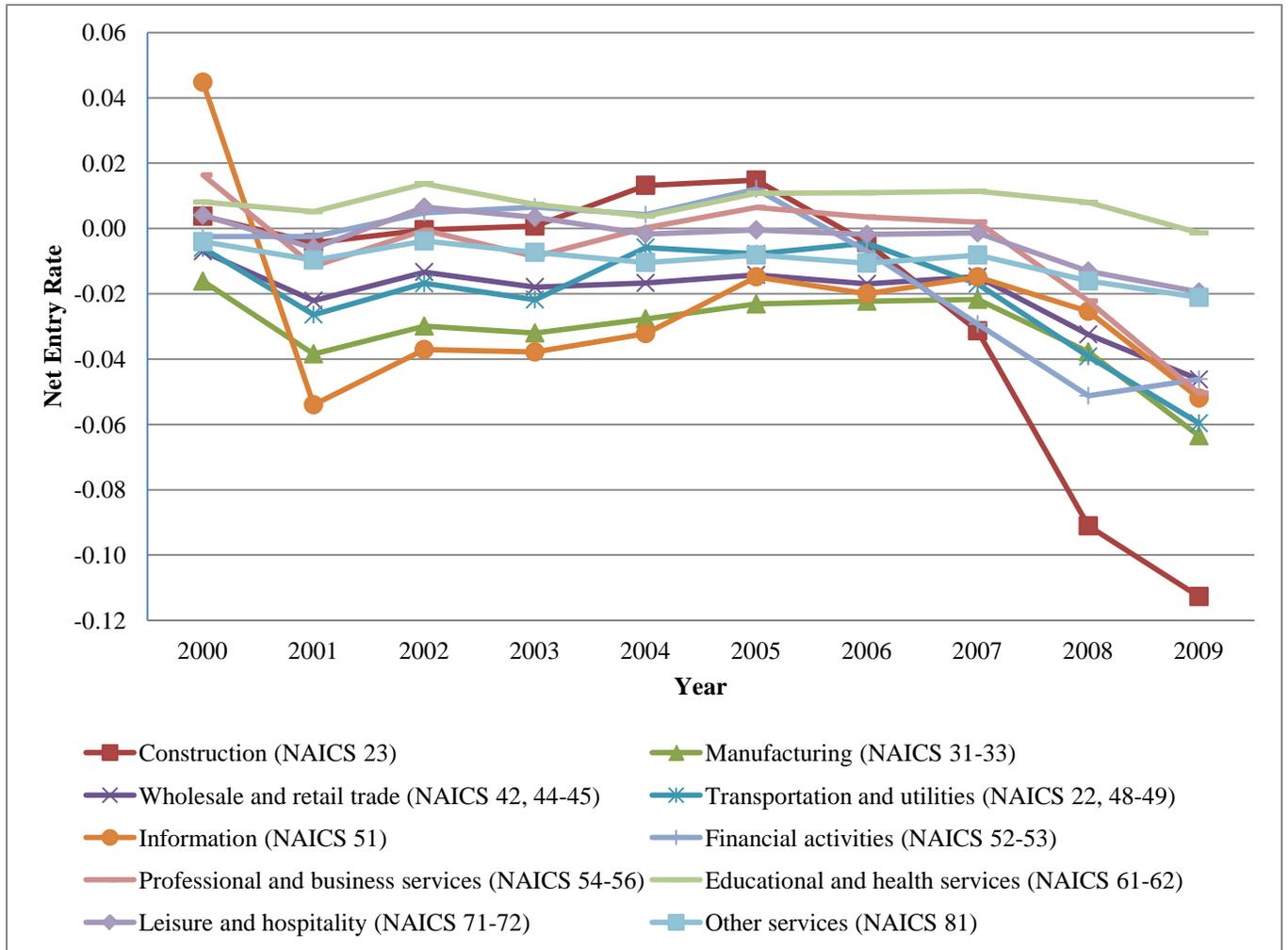
Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations

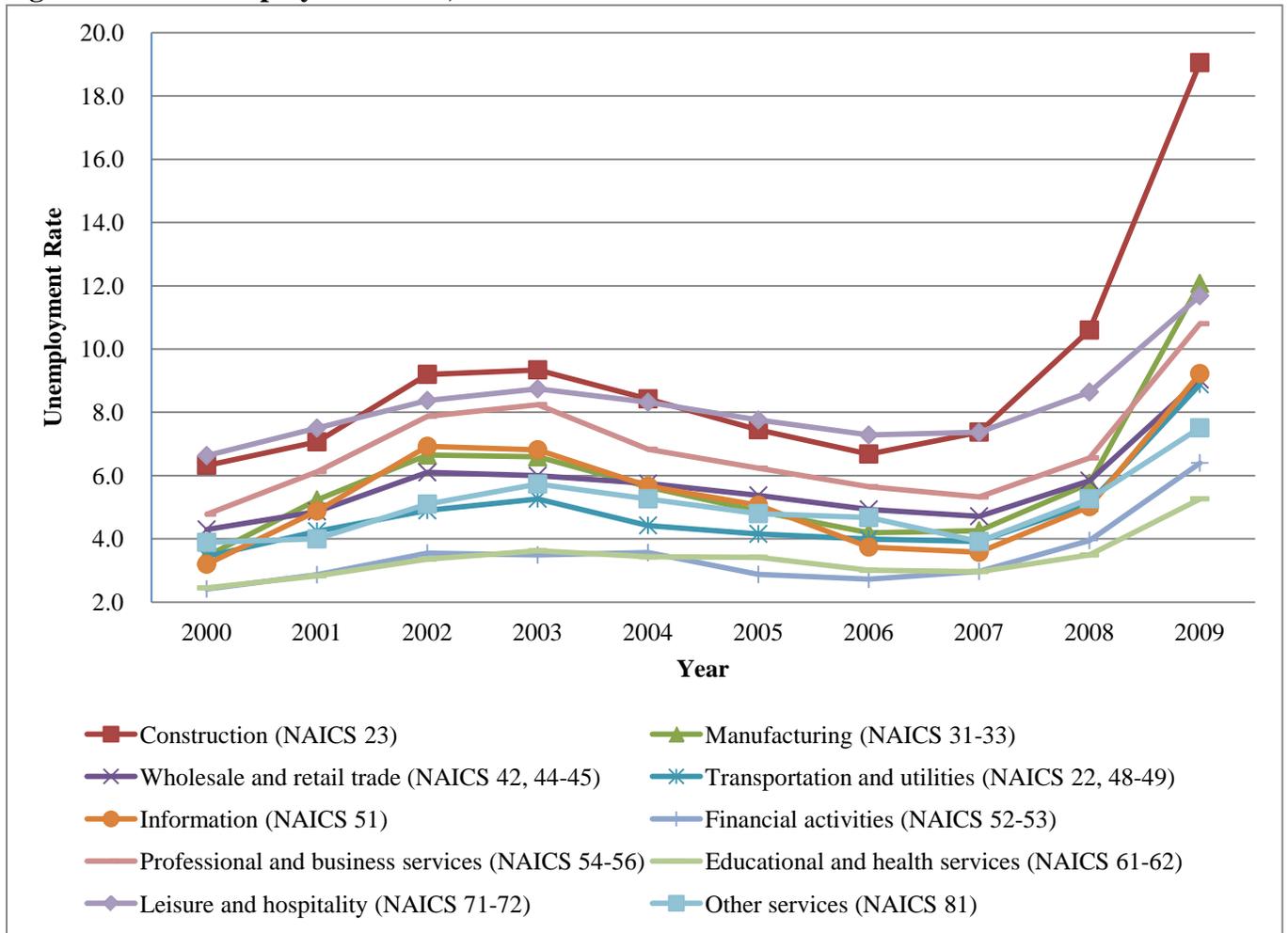
Appendix B: Figures

Figure 1: The Net Entry Rate, 2000-2009



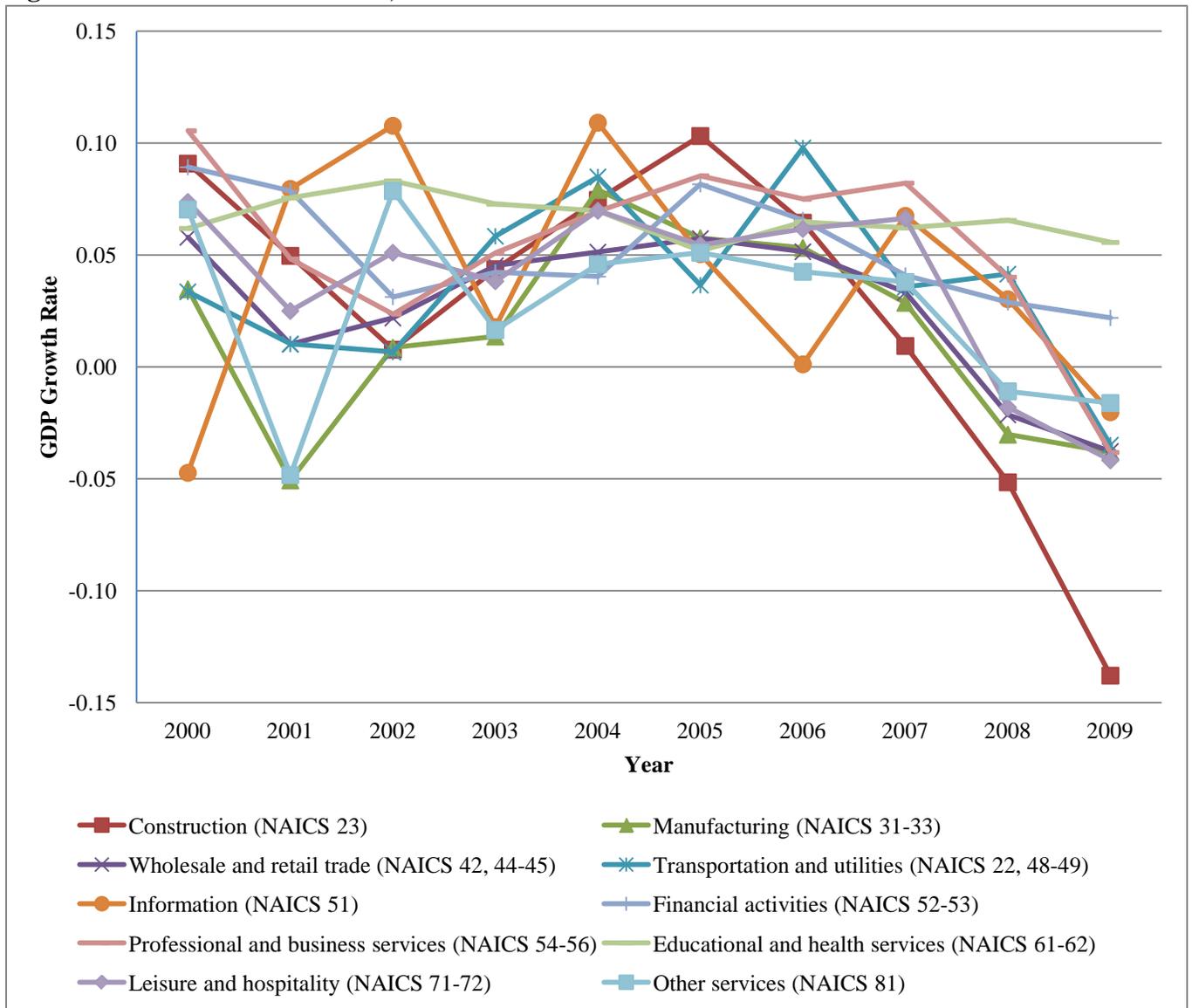
Source: Bureau of Labor Statistics (BLS) and author's calculations

Figure 2: The Unemployment Rate, 2000-2009



Source: Bureau of Labor Statistics (BLS) and author's calculations

Figure 3: The GDP Growth Rate, 2000-2009



Source: Bureau of Economic Analysis (BEA) and author's calculations