J Econ Growth (2006) 11:263–288
DOI 10.1007/s10887-006-9004-9

ORIGINAL ARTICLE

Scale effects in endogenous growth theory: an error of aggregation not specification

Christopher A. Laincz · Pietro F. Peretto

Published online: 28 October 2006
© Springer Science+Business Media, LLC 2006

Abstract Modern Schumpeterian growth theory focuses on the product line as the main locus of innovation and exploits endogenous product proliferation to sterilize the scale effect. The empirical core of this theory consists of two claims: (i) growth depends on average employment (i.e., employment per product line); (ii) average employment is scale invariant. We show that data on employment, R&D personnel, and the number of establishments in the US for the period 1964–2001 provide strong support for these claims. While employment and the total number of R&D workers increase with no apparent matching change in the long-run trend of productivity growth, employment and R&D employment per establishment exhibit no long-run trend. We also document that the number of establishments, employment and population exhibit a positive trend, while the ratio employment/establishment does not. Finally, we provide results of time series tests consistent with the predictions of these models.

Keywords Endogenous growth · R&D · Scale effects · Firm size · Establishments

JEL Codes E10 · L16 · O31 · O40

C. A. Laincz (✉)
Department of Economics, LeBow College of Business,
Drexel University, 32nd & Market Sts.,
Philadelphia, PA 19104,
USA

P. F. Peretto
Department of Economics, Duke University, Durham, NC 27710, USA

1 Introduction

The theory of endogenous growth developed in the past 15 years puts technological innovation at the forefront of explanations of differences in standards of living across countries and time. In so doing, it emphasizes features of the real world like imperfect competition, accumulation of intangibles, economies of scale, creative destruction, and the distinction between quality improvements and the creation of new products, that generate far-reaching policy implications. This connection between policy and the long-run growth rate constitutes, in our view, the main attraction of the theory and explains the variety of issues to which researchers have applied it; see for example the breadth of topics covered in Grossman and Helpman (1991) and Aghion and Howitt (1998).

Perhaps because it is the most visible consequence of increasing returns, tests of the theory tend to focus on the "scale effect" prediction of the models proposed by Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992). The strongest formulation of the critique is due to Jones (1995b). The scale effect says that an increase in the labor endowment of an economy leads to a higher growth rate of productivity. Jones points out that this prediction stems from the assumption that the growth rate of productivity is proportional to the number of scientists and engineers engaged in R&D. He then documents that this assumption is inconsistent with the time-series data on R&D inputs and outputs for the US. Most researchers—including us—accept his conclusion that this evidence points to a problem. There is disagreement, however, concerning the solution.

Two approaches have emerged. One posits decreasing returns to knowledge in order to avoid the scale effect. The proposed model features "semi-endogenous" growth in the sense that the steady-state level of productivity is endogenous and subject to policy action, while its growth rate is proportional to the growth rate (as opposed to the level) of R&D inputs which, in equilibrium, is pinned down by the (exogenous) population growth rate. This alteration of the theory fares no better when confronted with the empirical evidence (Aghion & Howitt, 1998, 2005; Ha & Howitt, 2006).

The second approach makes a substantial departure from the original formulation of the theory. The early models posit R&D technologies that feature proportionality of productivity growth to *aggregate* R&D inputs. In contrast, the models developed by Peretto (1996, 1998, 1999), Dinopoulos & Thompson (1998), Young (1998), Howitt (1999) and Peretto & Smulders (2002) shift the focus from the whole economy to the individual product line as the main locus of innovation. In such a disaggregated framework it is straightforward to dispose of the scale effect. A process of development of new product lines fragments the economy into submarkets whose size does not increase with population. This process sterilizes the effect of the size of the economy on firms' incentives to do R&D. The crucial features of this version of endogenous growth theory are that (i) growth depends on *average* R&D employment (i.e., R&D employment per product line) and (ii) average R&D employment is scale invariant. Feature (i) is a consequence of the assumption that innovation happens at the firm (product line) level, not at the economy level, while feature (ii) is a consequence of endogenous product proliferation driven by economic incentives.

These models emphasize the following mechanism. An increase in the aggregate level of employment allows existing firms to increase their size, but it simultaneously induces entry of new firms that draws labor away from incumbents. As a result, in the long run average firm size is invariant to the scale of the economy. The consequence of this process of market fragmentation is that fundamentals and policy variables that work through the size of the market do not affect steady-state growth (see, e.g., Peretto, 2003).

In this paper we study this mechanism using data on employment, R&D personnel, and the number of establishments in the US for the period 1964–2001. Previous studies have looked at the aggregate empirical implications of endogenous and semi-endogenous growth models (e.g., Aghion & Howitt, 2005; Dinopoulos & Thompson, 1999; Ha & Howitt, 2006 Jones, 1995a,b; Zachariadis, 2003) but have not looked at the salient feature of models that distinguish the firm-level knowledge production function from the aggregate. By focusing on the number of establishments we address explicitly the role played by the new variable introduced by these models.

Our data show that while the total number of R&D workers undoubtedly increases with no apparent matching change in the long-run trend of productivity growth, employment per establishment and R&D personnel per establishment exhibits no long-run trend. Moreover, models of this class predict that average firm size is positively related to growth. We provide results of time series tests consistent with this prediction. Finally, we document that the number of establishments, employment and population exhibit a positive trend, while the ratio employment/establishment does not. Thus, the prediction that establishment size is invariant to the scale of the economy appears quite reasonable and we cannot reject proportionality between employment and the number of establishments.

We present our argument below first by briefly reviewing various approaches to the scale effects in Sect. 2. Section 3 presents the data and Sect. 4 looks empirically at two basic results of these models. Section 5 concludes.

2 Scale effects in endogenous growth models

2.1 The problem

Consider a simplified model where Y is output, A is productivity, L is the size of the workforce, L_Y is labor used in producing output, L_A is labor engaged in R&D, and δ is a parameter governing R&D productivity:

$$Y = AL_Y; \tag{1}$$

$$\dot{A} = \delta L_A A; \qquad \delta > 0 \tag{2}$$

$$L_Y + L_A = L. \tag{3}$$

The first equation is the output production function; the second is the knowledge production function; and the third is the labor resource constraint.

In equilibrium, both activities employ some fraction of labor. Denote the share of the workforce engaged in R&D as s. In steady state s must be constant (and independent of L). The growth rate of income per capita, $y \equiv Y/L$, is

$$g_y = g_A = \delta s L. \tag{4}$$

According to this expression, an increase in the size of the workforce, L, raises the number of workers engaged in R&D and thus the growth rate g_y. Moreover, income per capita growth explodes with population growth.

These predictions cannot be reconciled with the data, except, perhaps, in very broad historical terms (see Kremer, 1993, and the discussion in Dinopoulos & Thompson,

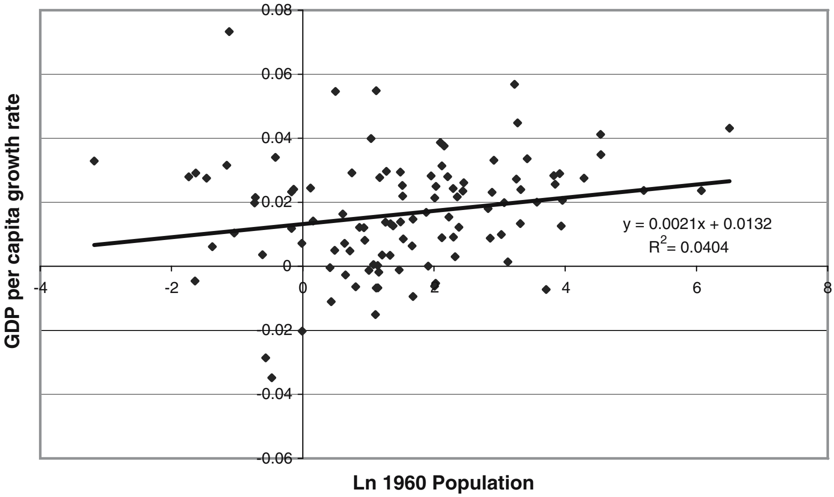

Fig. 1 GDP per capita growth rates and Ln 1960 population

1999). Figure 1 plots the natural log of the 1960 population levels against the real GDP per capita growth rates between 1960 and 2000 for 107 countries.[1] There is no signficant relationship between the two variables, the adjusted R^2 is only 0.04, even though the unconditional correlation appears to be positive. This result is in line with many other studies that look carefully at the conditional correlation between growth and population and do not find a significant relation (see, e.g., Backus, Kehoe, & Kehoe, 1992; Barro & Sala-i-Martin, 2004; Dinopoulos & Thompson, 1999).

The weakness of using cross-country evidence to evaluate closed economy models is, however, widely recognized. The better alternative is to examine time series behavior. One test is to compare average growth rates across periods over a long time horizon. Romer (1986) and Jones (1995a) take this approach finding higher growth rates in the post World War II era than before the inter-War period. Even more convincingly, Ben-David and Papell (1995) allow for endogenously determined structural breaks. They find growth rates increased in the Post-World War I era for most countries, and after the Great Depression for most others. While the evidence suggests some increase in growth rates of per capita GDP over a long-time horizon, the tests do not provide any information on the sources of higher growth rates. Ben-David and Papell point out that the structural breaks in the time series represent periods of upheaval when strong coalitions can be broken leading to a more efficient allocation of resources. Increases in trade openness could just as easily explain the change in growth rates. Thus, while rising growth rates over time are consistent with models with scale effects, alternative explanations are possible.

A third approach is to focus on the time-series data for the US alone, as the world's leading R&D performer. (The exercise can be easily extended to the leading OECD countries.) And this reveals the problem. Figure 2 graphs the total amount of employment in the US economy from 1964 to 2000 taken from County Business Patterns, and contrasts it with the growth rate of the Private Business Productivity Index (PBP) re-

[1] The source is the Penn World Tables 6.1 (Heston, Summers, and Aten, 2001). For Germany, 1970 is the starting point as the 1960 values not included in the Penn World Tables.

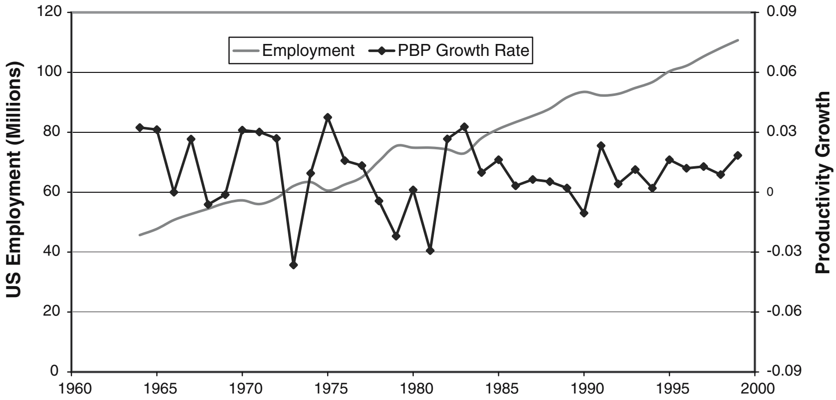

Fig. 2 Employment and Private Business Productivity Growth Rate
Data: Employment data are from County Business Patterns. The Private Business Productivity Index Growth Rate is calculated from the Private Business Productivity Index from the Bureau of Labor Statistics.

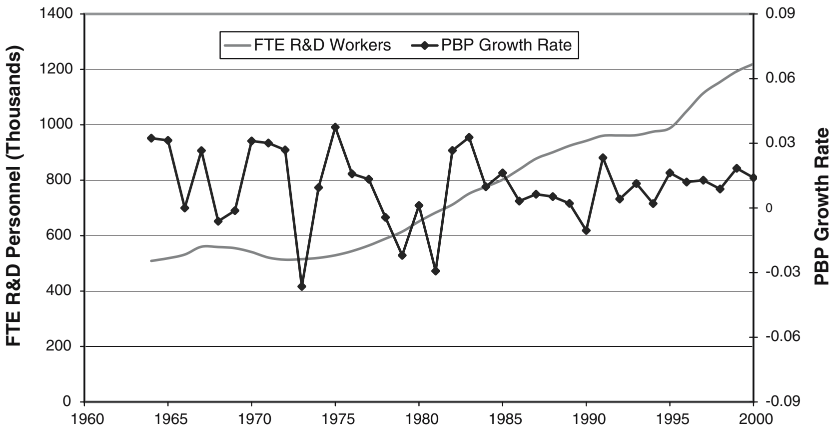

Fig. 3 Total FTE R&D Personnel and Productivity Growth
Data: FTE R&D Personnel data are from the Statistical Abstracts of the US. The Private Business Productivity Index Growth Rate is calculated from the Private Business Productivity Index from the Bureau of Labor Statistics.

ported by the Bureau of Labor Statistics (BLS). Clearly, PBP growth shows no significant upward or downward trend while total employment over that period grows at an average annual rate of 2.53%. Figure 3 shows the same productivity measure against the total number of R&D personnel over the period 1964–1997. The total number of personnel devoted to research grows at an annual rate of 2.40%. The basic story is clear. There is an increasing trend in the total personnel and R&D personnel, but productivity growth shows no obvious increases as predicted by models with scale effects.

If the scale effect prediction is not consistent with the data, but we wish to retain the appealing feature of these models that steady-state productivity growth is endogenous, then where exactly does the scale effect problem lie? One argument contends that the constant returns to scale assumption in (2) drives the result and the function is misspecified. The solution is to introduce diminishing returns to knowledge in the knowledge production function. A different approach observes that Eq.(2) implies that if there are, say, one million scientists and engineers in the economy, allocating them to one million firms or or to just one single firm has no effect on the growth rate of the economy. In contrast, if knowledge creation takes place at the firm level, then each firm's contribution to the stock of knowledge depends on its size and the number of firms matters. Therefore, the scale effect problem follows from failing to account for how the economy allocates its resources across productive units. We now turn to discussing the implications of these two theoretical arguments.

2.2 Solution 1: decreasing returns to knowledge

The first approach that we consider assumes that R&D becomes more difficult as the knowledge stock grows (Jones, 1995b; Kortum, 1997; Segerstrom, 1998). These models predict that policy has no impact on long-run growth rates; it only affects the transition path. To see this, we modify Eq. (2) as follows:

$$\dot{A} = \delta L_A A^{\phi}, \quad 0 < \phi < 1. \tag{5}$$

The new parameter ϕ captures the fact that innovations building on past discoveries become progressively harder, i.e., the knowledge production function exhibits decreasing returns to knowledge. Accordingly, productivity growth is given by

$$\frac{\dot{A}}{A} = \delta L_A A^{\phi-1},$$

and along the balanced-growth path with constant s we have

$$g_y = \frac{n}{1-\phi}, \quad n > 0 \tag{6}$$

where n is the growth rate of the population. The model now yields that the rate of growth of income per capita is proportional to the population *growth rate* as opposed to the population *level*. Figure 4 plots population growth rates against real GDP per capita growth using the Penn World Tables. As in Fig. 1, no significant relationship emerges, even though basic trend lines show that the unconditional correlation is negative. Summarizing the most recent evidence, Barro and Sala-i-Martin (2004, chapter 12) use the total fertility rate as a proxy for population growth and show that cross-country regressions produce a negative and significant conditional correlation between income per capita growth and population growth.

The model sketched above produces a different relationship between growth and the size of the population. Specifically, the fraction of the population conducting research, sL, affects the level of income per capita in a manner similar to the Solow model. Looking at the transition to the steady-state, per capita income at time t is

$$y(t) = (1-s)\left(\frac{\delta(1-\phi)}{n} sL(t)\right)^{1/(1-\phi)}.$$

Taking logs and time-derivatives, we find that

$$\frac{\dot{y}}{y} = \frac{1}{1-\phi}\left(n - \frac{\dot{n}}{n}\right), \tag{7}$$

which says that rate of growth of income per capita is positively related to the rate of growth of the population, but negatively related to the rate of change in the population growth rate.

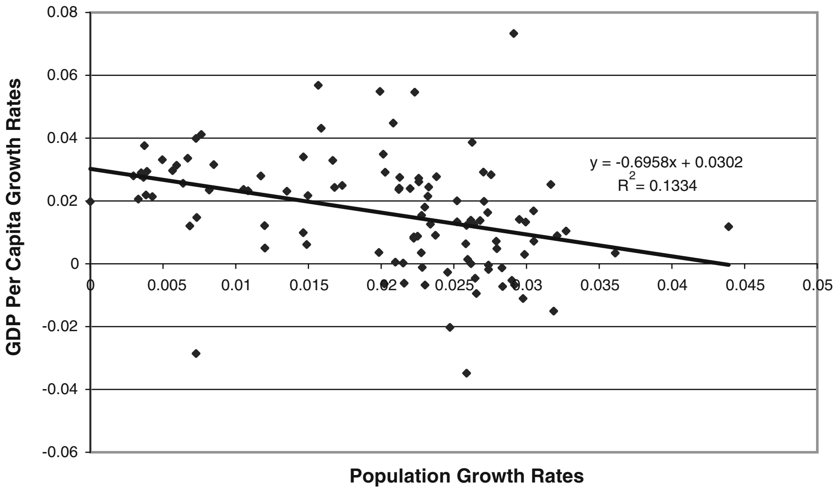

Fig. 4 GDP per capita growth and population growth rates

Using time series data for the US, Aghion and Howitt (2005) find no evidence of a proportional relationship between productivity growth and the growth rate of R&D inputs. Ha and Howitt (2006) go further. They find that the semi-endogenous growth model fares poorly when confronted with US time series data covering the last half of the twentieth century. The main problem is that in the presence of stable population growth, the model predicts an inverted-U-shaped pattern for productivity growth while the data display a regular U-shaped curve. In fact, they find that the model performs best when $\phi = 1$, precisely the value the theory seeks to avoid. Other work casts doubt on this class of models. Porter and Stern (2000) use international patent data to construct both global and country-level knowledge production functions to estimate ϕ, thereby controlling for the presence of international spillovers as emphasized by Klenow and Rodríguez-Clare (2005). This is arguably the most comprehensive cross-country study of the aggregate knowledge production function. Porter and Stern cannot reject constant returns ($\phi = 1$).

Beyond their results, we can turn to the huge body of empirical work by economists and demographers on the relationship between growth and population and ask if the evidence supports the prediction that population growth and income per capita growth are positively correlated. The answer is no. In fact, Kelley and Schmidt (2003) begin their survey of economic and demographic change by quite clearly stating: "No empirical finding has been more important to conditioning the 'population debate' than the widely-obtained statistical result showing a general *lack* of correlation between the growth rates of population and per capita output" (emphasis in the original). They then conclude that, if anything, there appears to be a negative relationship between population growth and income per capita growth in data covering the last two decades. They repeatedly caution, however, that one should not draw strong conclusions from this evidence because the relationship displays remarkable instability across different time periods.

In addition, one of the key implications of this class of models is that policy changes have only level effects on GDP per capita not growth effects. Hence the term "semi-endogenous" growth to describe the feature that these models incorporate the production of A but that policy action cannot alter its long-run growth rate. Kocherlakota and Yi (1997) examine the time-series data for the US and UK separately rather than appealing to cross-country regressions. They look at the effect of taxation and public expenditure on the long-run growth rates. They argue that if policy has no effect the sum of the coefficients on the policy variables should be zero. However, they find that both coefficients are significant and that the sum is significantly different from zero. They interpret these findings to mean that policy does indeed have long-run effects on growth rates in contrast to the prediction of semi-endogenous growth models.

2.3 Solution 2: firm-specific knowledge production

The second approach to eliminating the scale effects allows for expansion in the number of firms (or varieties of products). To illustrate this mechanism, we modify the model of Sec. 2.1 as follows:

$$Y = \left[\int_0^F Y_i^{\frac{1}{\theta}} di\right]^\theta, \quad Y_i = A_i L_{Y_i}, \quad \theta > 1 \tag{8}$$

$$\dot{A}_i = \delta L_{A_i} A; \quad A = \int_0^F \frac{A_j}{F} dj, \quad \delta > 0 \tag{9}$$

$$\int_0^F \left(L_{Y_i} + L_{A_i}\right) di = L. \tag{10}$$

The subscript i refers to each firm. The first line specifies output as the aggregation of individual outputs. The second specifies R&D at the firm level. This setup assigns a very important role to the knowledge aggregator, A, that describes the productivity of labor in R&D. According to this aggregator each firm contributes to the pool of general knowledge that allows the entire economy to grow.[2] The third equation is the aggregate resources constraint.

It is customary in this line of work to posit that each product line i is dominated by a local monopolist so that there is a one-for-one correspondence between product variety and the number of firms. We wish to stress that this feature is not really an assumption but a consequence of the fact that entry is costly, so that entrepreneurs investing resources to create new products do not target existing product lines because entering in direct price competition with the existing incumbent leads to losses. In other words, each product line is a natural monopoly in the sense that in equilibrium it can accommodate only one firm earning positive profits. [3] Hence, new

[2] The spillover mechanism varies across models, but the result is the same. In Peretto (1999) knowledge is sector-specific and there are no spillovers across sectors; in Peretto (1998) and Dinopoulos and Thompson (1998) spillovers depend on average knowledge; in Young (1998) and Howitt (1999) spillovers depend on the knowledge level of the frontier firms. Peretto and Smulders (2002) argue that for a general spillovers function $A = h\left(A_1, \ldots, A_F\right)$, scale effects vanish asymptotically as F grows large as long as the operator $h(\cdot)$ converges to the arithmetic average. They also provide a model based on the concept of localized spillover networks that produces such an operator h as the result of an economic mechanism.

[3] The argument is actually stronger. If one assumes that production entails fixed operating costs so that the individual firm's technology is $Y_i = A_i\left(L_{Y_i} - \kappa\right)$, where κ is a fixed cost in units of labor, then the individual product line is a natural monopoly even without entry costs. See Peretto and Connolly (2004) for a recent discussion of the implications of fixed operating costs in endogenous growth theory.

firms supply new products and along the growth path of the economy the number of firms is always equal to the number of products.[4]

The substantial change to the basic model is the disaggregation of production and R&D decisions to the firm level. The key new variable, therefore, is the *endogenous* number of firms F. To bring out this feature, we focus on a symmetric equilibrium and let variables without the subscript denote averages. Thus, we can write aggregate output as

$$Y = F^{\theta} A L_Y,$$

where A stands for average productivity and L_Y for average employment in production. Average productivity evolves according to

$$\frac{\dot{A}}{A} = \delta L_A, \tag{11}$$

where L_A is average R&D. Thus, the functional forms of Sect. 2.1 now apply at the firm level. This change of relevant unit of analysis has profound implications. Again, let s denote the share of labor allocated to R&D. In steady state s is constant and independent of L. Differentiating yields

$$g_y = (\theta - 1)\frac{\dot{F}}{F} + g_A.$$

For the sole purpose of illustration, suppose that in equilibrium the number of firms is proportional to employment, i.e., $F = \eta L$, where η is a constant. Then,

$$g_y = (\theta - 1)\, n + \delta L_A.$$

Now use the resources constraint to write

$$g_y = (\theta - 1)\, n + \delta s \frac{L}{F} = (\theta - 1)\, n + \delta s \eta^{-1}. \tag{12}$$

As one can see, income per capita growth no longer depends on L. Moreover, its dependence on population growth n is no longer necessary. For example, if the output aggregator in (8) did not feature the love-of-variety (specialization) effect we would set $\theta = 1$ in the equation above without eliminating endogenous growth.

Finally, income per capita growth is positively related to the average firm size, $\frac{L}{F}$. This is important. It tells us that these models eliminate the scale effect because they focus on the scale of the firm (product line), as opposed to the scale of the economy.

To summarize, this approach produces two testable predictions: (i) long-run average R&D and average firm size are constant and (ii) increases in average firm size yield higher growth rates. The next section confronts these predictions with the data.

Perhaps at this stage it is worth commenting on the posited proportionality between the number of firms and employment because the issue has been raised elsewhere

[4] An interesting case that might provide an exception to this rule is that of multiproduct firms. We are not aware of work along these lines except for a short section in Smulders and van de Klundert (1995). We point out, moreover, that the models discussed in the literature do not allow for economies of scope across product lines within a single firm, exactly like our setup above, so that they typically yield the single-product firm as a feature of the equilibrium rather than as an assumption. (Especially if there are fixed operating costs per product line.) We spare the reader the details and posit directly the correspondence between product variety and number of firms. The important point is that doing so is just the equivalent of positing a constant share of employment allocated to R&D without deriving it from first-order and market equilibrium conditions.

in the literature (Jones, 1999). The relation $F = \eta L$ might induce one to conclude that this class of models requires another "knife-edge" condition in that one needs to assume that the number of firms is exactly proportional to population. To address this concern we offer two arguments. The first, and more important, is empirical: in our data presented below the number of establishments is proportional to employment.

The second argument is that in all of these models the proportionality between the number of product lines (firms) and the size of the workforce is a result of an economic mechanism. A simple example works as follows (see, e.g., Peretto, 1998). In the economy described by Eqs. (8)–(10) the value of aggregate output is equal to total consumption expenditure, $P_Y Y = E$. Imagine that consumers have logarithmic preferences so that their saving behavior is represented by the Euler equation $r = \rho + \dot{E}/E$, where r is the interest rate. Further, imagine that there exists a technology for the creation of new goods of the form

$$\dot{F} = \beta L_N, \qquad \beta > 0.$$

We now take the wage as the economy's numeraire, $w = 1$. We then let $\epsilon \equiv \frac{\theta}{\theta - 1}$ denote the elasticity of substitution between products in (8), and compute the returns to productivity-enhancing and variety-expanding R&D implied by our primitives:

$$r = \delta \left[\frac{P_Y Y (\epsilon - 1)}{\epsilon F} - L_A \right];$$
$$r = \beta \left[\frac{P_Y Y}{\epsilon F} - L_A \right].$$

In steady state, $\dot{E} = 0$ and $r = \rho$. Moreover, the properties of the CES aggregator (8) and the prices set by firms yield $E = P_Y Y = AFL_Y$. If we retain the assumption that the economy allocates a constant share, s, of labor to research activity, we have $FL_Y = (1 - s) L$. We then solve these equations for

$$F = \eta L, \qquad \eta \equiv \frac{1 - s}{\rho \left(\frac{1}{\delta} - \frac{1}{\beta} \right)}.$$

The analysis highlights that the proportionality of the number of firms to population is a natural equilibrium outcome when profits per firm are proportional to the inverse of the number of firms, and the cost of variety creation is constant.

We wish to stress that in this paper we focus on the core innovation of a large class of models—namely, that long-run growth is independent of scale because of endogenous product proliferation—and thus in our representation of the theory we focus on the basic model abstracting from several issues such as spillovers, composition effects, oligopolistic market power, fixed operating costs as opposed to sunk costs, international trade, endogenous population growth, that have been discussed in detail in the literature (see Aghion & Howitt, 1998, 2005; Galor, 2005; Jones, 2005; Peretto & Connolly, 2004; Peretto & Smulders, 2002). The reason is that all of these extensions are not needed to illustrate the main thrust of the theory and trying to incorporate their role would only complicate the presentation without adding insight.

An important issue that we do not incorporate formally in our representation of the theory but on which we do want to comment is that of transitional dynamics. As we claim above, the proportional relation between the number of firms and the size of the labor force is the outcome of an economics mechanism driven by costly entry (see, e.g., Dinopoulos & Thompson, 1998; Peretto, 1998; Peretto & Smulders, 2002). Specifically, the theory's predictions about what happens over time in response to shocks take into account the difference between the economy's instantaneous response, where the number of firms is given, and the long run, where the number of firms adjusts endogenously. For example, Peretto (1998) shows that if the economy is subject to an increase in population, the growth rate jumps up because the larger labor force is initially absorbed by the existing firms that thus become larger and do more R&D. Over time, new firms enter and draw workers away from existing firms. As a result of this fragmentation process the growth rate gradually slows down and eventually reverts to the original steady-state value independent of population. In other words, in the long run the increase in population is fully absorbed by the number of firms leaving firm size and thus growth unaffected.

These transitional dynamics must be kept in mind when looking at the data because it clearly implies that trying to match the behavior of the relevant series only to the steady state of the models can be quite misleading. As we show below, despite the fact that our series on firm size and growth do not appear to have a secular trend, there are movements that clearly suggest that we must take into account the economy's long-run response to exogenous shocks. Thus, even though in our discussion we focus mainly on the steady-state predictions of the theories that we compare, when appropriate we shall discuss the implications for transitional dynamics of the firm-based theory.

3 Data

3.1 Measuring variety

A careful empirical evaluation of theories of long-run growth must start from the identification of the appropriate unit of analysis. The elimination of the scale effect, and the consequent preservation of the long-run policy implications of endogenous growth theory, stems from the incentives for new productive units to emerge and supply new "varieties." The question then is how one defines a variety empirically.

The theories we are interested in divide the economy into product lines. Unfortunately, we do not have data on product lines. However, the micro-level knowledge production function corresponds to both an individual product line and an individual firm. Given this correspondence, it is natural to look for data on the number of firms. The U.S. Census Bureau publishes data on (1) the number of enterprises and (2) the number of establishments. An enterprise (firm) is defined as a "business organization under a single management and may include one or more establishments." Establishments refer to physical locations, that is, individual production plants.

Strong micro-level evidence suggests that productivity and R&D only weakly correspond to firm size once plant and business unit levels are taken into account. Adams & Jaffe (1996) provide evidence that R&D per plant, not per firm, drives productivity growth. They find that productivity increases from R&D at the firm level are diluted once the number of plants are included in the regression. Similarly, Cohen & Klepper (1996) find that the relationship between R&D and firm size weakens significantly when controlling for business unit size. The evidence points to innovation taking place at the plant level. The models that we wish to test focus on individual production units, so that the establishment corresponds better to the notional variable that drives the mechanism that we want to investigate.

Furthermore, multi-plant firms do not pose a particular problem. When we turn to the data below the number of firms and number of establishments clearly track one another quite closely. The reason for this close correspondence is that the vast majority of firms operate a single plant that produces a single product. Dunne, Roberts, and Samuelson (1988) report that between 1963 and 1982 single-plant firms in manufacturing constituted 93% of all firms and operated in only slightly more than one 4-digit SIC industry on average. Multi-plant firms operated in 2–4 industries on average with about 3.5 plants per firm, which yields about one plant per industry. Even in those few cases, such as automobiles, each plant tends to produce a single variety. There are, of course, some instances where plants do produce multiple products (e.g., batch processing in the chemical industry), but as a measure of the key varable in the theory establishments is probably the best proxy available at this time.

Alternative approaches to variety exist in the literature. One option is to interpret variety as literally the number of goods that enter the utility function of a representative consumer or the production function of a representative producer. A novel approach to the analysis of this type of variety expansion has emerged recently in the trade literature, sparked by the work of Feenstra (1994) who developed a method for computing the effect of new varieties on the exact price index of a single (composite) good. Broda and Weinstein (2006), for example, measure the welfare effects of variety expansion of U.S. imports in the period 1972–2001. They define a variety as a product–country pair, where the products are defined by the trade code categories. This implies that products produced by the same firm at plants located in different countries are different varieties.

Klenow and Bils (2001) take a slightly different approach and look at how frequently the Bureau of Labor Statistics changes items in the representative basket of goods for conducting CPI calculations. They thus focus on the pattern of substitution between "old" and "new" goods by consumers and infer growth of product variety from changes in the price indices of groups of goods.

These papers provide interesting results from a welfare point of view, but move the focus away from the basic mechanism highlighted by the class of models that we are interested in. Specifically, neither approach sheds light on the elimination of the scale effect through the proliferation of product lines each one dominated by a firm that engages in R&D aimed at increasing its own productivity. Since the key element of this mechanism is the allocation of resources across product lines, we contend that focussing on production units—as opposed to goods—is the more appropriate approach for evaluating it empirically. We find interesting, however, that based on their best estimates Klenow and Bils conclude that product variety in the US grew on the order of 1% over the period 1959 to 1999—which happens to be the same as the population growth rate, exactly as predicted by the theory outlined above!

3.2 Enterprise and establishment data

The Enterprise Statistics series from the US Census Bureaus is compiled alongside the 5-year Economic Census. The series started in 1954, continued in 1958 and 1963, and then from 1967 onward every 5 years until 1992. 1954 data were not available. Funding was discontinued for Enterprise Statistics in 1997. Figure 5 shows the average employment per enterprise based on the data available from the Enterprise

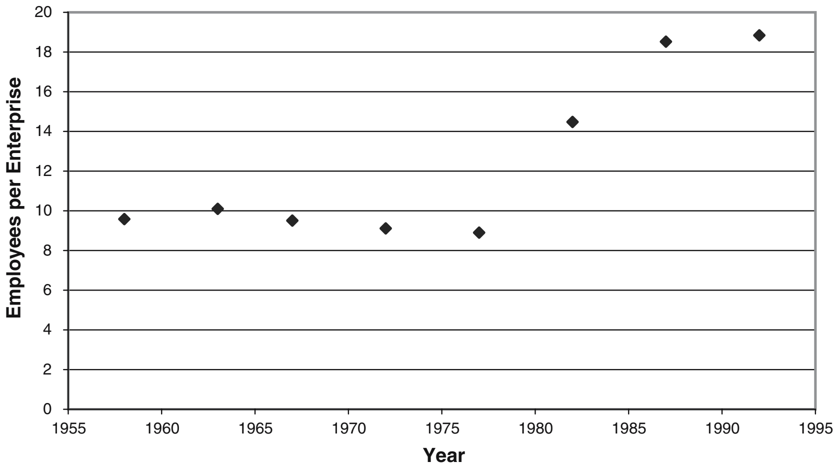

Fig. 5 Employees per Enterprise From US Census Enterprise Statistics

Statistics program which record both number of enterprises and employment. Note the sudden upward jumps in the figures in 1982 and 1987. Part, if not the majority of this sudden upward movement, can be explained by the increase in the types of enterprises included or excluded. In 1977, the census reported "all companies" as including both those with and without annual payrolls, but in 1982 it includes only companies with an annual payroll, thereby excluding many small firms. In 1987 agricultural production was excluded. In addition, the 1987 data include companies who report Federal income tax in the following categories: Trucking and Courier Service, Water Transportation, Transportation Services, and Hospitals.

Figure 6 shows data from 1988 to 2001 available on the US Small Business Administration website which tracks employees, enterprises *and* establishments annually. Since 1988, both average enterprise and average establishment size have been growing in a near parallel fashion. Note that the SBA data uses the County Business Patterns data, the same data we use for the rest of the paper. The important piece of information to extract from Fig. 6 is the clear comovement of the two series. Establishments per enterprise remained at 1.2 throughout the 1988–2001 period with very little change despite the high growth period for the US economy and remarkable in light of the increase in employment per establishment of 11% as shown in Fig. 6. While we contend that the establishment, not the enterprise is the more appropriate unit of analysis for the reasons given above, these numbers suggest that, provided there were no major changes in the establishments per enterprise behavior in the preceding decades, employees per establishment serves as a useful proxy for enterprise size.

Beyond the evidence provided by Dunne et al. (1988) cited above, the Bureau of the Census calculates the percentage of each establishment's shipments that are classified within its designated 4-digit industry, and this number is typically above 90%, implying that the vast majority of plants produce one product.[5] Furthermore,

[5] The Census actually calculates two measures: (1) the specialization ratio is the portion of industry shipments accounted for by the primary products of establishments classified in that industry; (2) the coverage ratio is the portion of product shipments accounted for by the establishments classified in the industry. The simple averages for the specialization and coverage ratios for 1992 across 4-digit

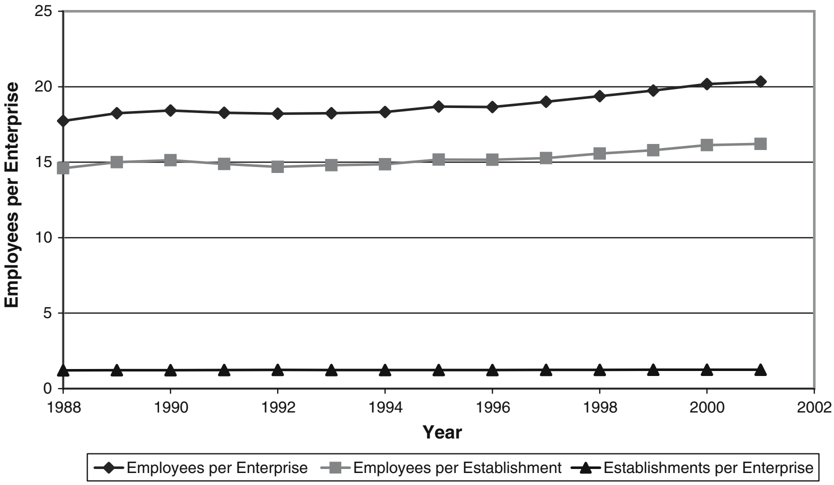

Fig. 6 Employees per Enterprise and Establishment SBA Data (1988–2001)

the percentage of single-plant firms out of the total and the average number of plants per multiplant firm hardly changed over the decades preceding the data in Fig. 6. This tells us that manufacturing is mostly populated by single-plant, single product firms.

Available international data are, unfortunately, quite limited. In Table 1 we present the available time series from the OECD Firm-Level Project. The project includes 10 OECD countries including those shown plus West Germany (for which data were not available). The coverage in terms of years varies by economy. The data contain employees and numbers of firms excluding single-person businesses. In addition, the data take the firm as the unit of analysis, except for Germany where only establishment level data are available, and Finland where data are reported at the firm and establishment level.

Because of the limited time period, it is difficult to say much about the stability of the average firm size over time. However, most countries appear to have fairly stable firm size with two potential exceptions. Both Portugal and the UK exhibit significant declines in average firm size. Portugal underwent significant labor market deregulation and a period of privatization beginning in the mid-1980s which may explain the decline. Clearly though, the striking feature is the large disparity across nations which raises many interrelated questions such as: Why the large disparity? What is the connection between these differences and economic growth? The latter question is the subject of Pagano and Schivardi (2003) which investigates this aspect using Eurostat data. They find that average firm size is positively correlated with growth even after controlling for potential reverse causality running from growth to firm size. However, their study can only examine the early 1990s because of data limitations.

Footnote 5 continued
sectors were 91.9 and 90.6, respectively. The median value is 93 for both. Data for 1997 and later are not available. About 10% of the industry groups have missing data for 1992, but if we use the 1987 data available for these missing figures, leaving less than 1% of industry groups without data, the averages marginally change to 92.1 and 90.6, while the median values remain exactly the same. Weighting each sector by the number of establishments increases the specialization and coverage ratios to 93.3 and 92.2 Unfortunately, similar statistics at a higher level of disaggregation (5, 6 or 7 digits) are not available.

Table 1 Average employees per firm of OECD countries

Year	Canada	Denmark	Finland	France	Italy	Netherlands	Portugal	UK	US
1981		10.1							
1982		10.1							
1983		10.1					19.5		
1984	9.7	10.5					19.0		
1985	9.7	10.9					18.3		
1986	9.7	11.5					17.6	33.8	
1987	10.0	11.5			9.4		17.3	33.6	
1988	10.4	11.4	11.3		9.4		16.1	32.9	
1989	10.6	11.6	10.4		9.5		15.6	32.2	21.4
1990	10.3	11.7	11.2	29.9	9.7		15.6	32.6	22.9
1991	10.1	11.7	10.1	29.1	9.6		14.9	31.5	22.5
1992	9.8	11.7	10.8	27.5	9.2		14.1		27.4
1993	9.6	11.8	10.7	26.5	9.2	5.7	13.2	28.1	22.2
1994	9.6	12.1	10.7	25.8		6.1	11.9	27.0	21.9
1995	9.9		10.2	27.0		6.3		25.7	22.2
1996	10.2		10.0	28.4		6.7		25.6	22.2
1997	10.6		10.3			6.8		25.7	
1998								25.3	
Average over period	10.0	11.2	10.6	27.7	9.4	6.3	16.1	29.5	22.8

Source: OECD firm-level project data available at the OECD website

4 Results

As discussed in Sect. 2, the models that we are interested in testing produce two predictions: (i) long-run average R&D and average firm size are constant and (ii) increases in average firm size yield higher growth rates. We now look at what our data tells us.

4.1 Are long-run average R&D and firm size constant?

Figure 7 shows employment, population, R&D personnel, and the number of establishments. All four series grow over time at comparable rates.[6] Figure 8 illustrates the main implication of this fact. Employees per establishment and R&D personnel per establishment do not display any significant trend over the entire sample period. There is evidence of some shorter-run swings that, we argue, call attention to the transitional dynamic properties of the theoretical models. Figure 9 shows that the stability of per-establishment variables contrast with the upward trend in the participation rate for the entire population and the long-run fall in population per establishment. Interestingly, the latter two changes offset each other so that there is no trend in employment per establishment and in the ratio of R&D personnel to employment. In other words, the R&D share exhibits no trend.

Figure 10 looks at the per establishment variables more closely. Cursory inspection suggests several possible interpretations for the long-run behavior of employees and R&D personnel per establishment. One could argue that employees and R&D personnel per establishment do exhibit a positive growth trend and the events of the

[6] Total establishments in the economy and employees are from County Business Patterns and cover 1964–2000. R&D personnel data are from the National Science Foundation.

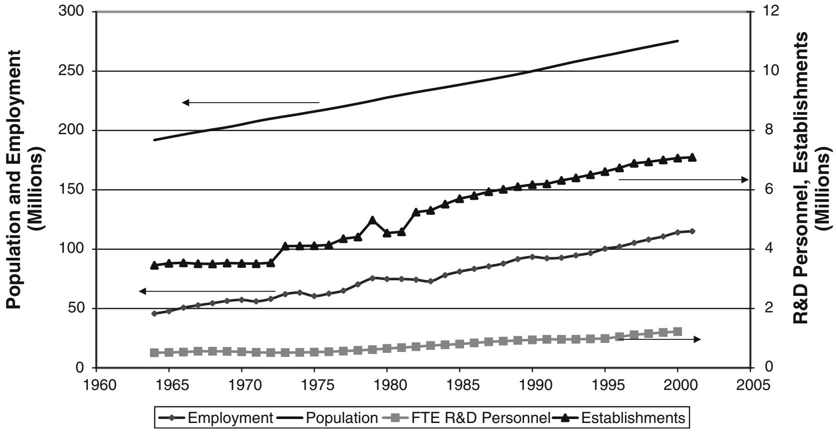

Fig. 7 Population, Employment, R&D Personnel, and Establishments
Data: Sources for employment and establishments are from County Business Patterns. FTE R&D Personnel data are from the Statistical Abstracts of the US. Population data are from the Penn World Table 6.1.

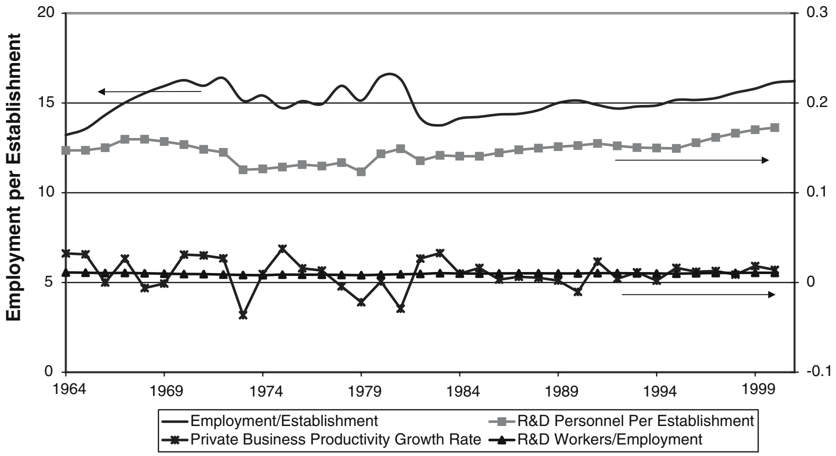

Fig. 8 Employees and R&D Workers per Establishment with Private Business Productivity Growth
Data: Employment and Establishments are from County Business Patterns. FTE R&D Personnel data are from the Statistical Abstracts of the US. Population is from the Penn World Tables 6.1. The PBP productivity index is from the BLS.

1970s were a mere aberration and increased growth will continue. R&D employment per establishment did not exceed the mid-1960s levels again until 1999. Under this scenario, employees per establishment will continue to grow in the coming decades exceeding the peak levels of the mid-1960s. Alternatively, what we see in the data is the economy's response to an exogenous shock. Following the adverse events of the 1970s, R&D personnel per establishment fell and then slowly returned to its steady-state level. This interpretation is consistent with the transitional dynamics of the firm-based theories discussed above.

Table 2 shows the results from simple time trend tests on employees per establishment and R&D workers per establishment. The tests show no evidence of a time trend

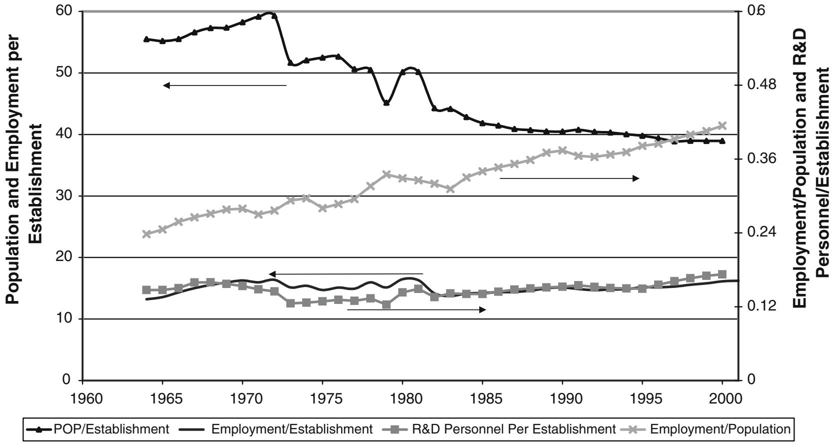

Fig. 9 Per Establishment
Data: Sources for Employment and Establishments are from County Business Patterns. FTE R&D Personnel data are from the Statistical Abstracts of the US. Population data are from the Penn World Table 6.1.

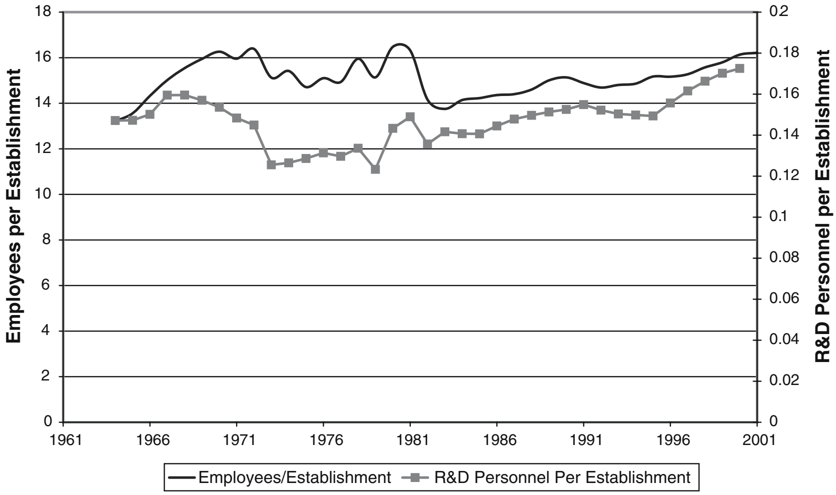

Fig. 10 Per Establishment
Data: Employment and Establishments are from County Business Patterns. FTE R&D Personnal data are from the Statistical Abstracts of the US.

in employees per establishment. The ADF test (2) rejects the unit root at the 10% level, but not quite at the 5% level for employees per establishment. For the R&D personnel per establishment, however, we cannot reject a unit root, though the time trend test is not significant at the standard levels. Both variables appear quite stable and exhibit little evidence of a trend in either direction, although data for the next few decades should help clarify whether there is a trend or not. A straight test of level stationarity for both employees and R&D workers per establishments cannot reject stationarity. Testing both series using the Kwiatkowski–Phillips–Schmidt–Shin

Table 2 Tests of trends in employees/establishment and R&D personnel/establishment

	Employees/establishment	Coefficient	Test-statistic	*P*-value
1	Time trend	0.01085	0.895	0.377
2	ADF test R&D personnel/ establishment	−0.336	−2.937	0.06
3	Time trend	0.000212	1.168	0.251
4	ADF test	−0.177	−1.410	0.169

The null hypothesis for the time trend tests is no time trend. The null hypotheses for the ADF tests is that the variable contains a unit root. Both ADF tests were conducted with a constant only and no time trend. Lags were chosen by the Schwarz Information Criterion. The ADF critical values for employees per establishment are −2.6092 for the 10% level, −2.9422 for the 5% level, and −3.6171 for the 1% level. The ADF critical values for R&D personnel per establishment are −2.6105 for the 10% level, −2.9446 for the 5% level, and −3.6228 for the 1% level

Data and Sources: Employees and establishments are from the County Business Patterns data and cover the years 1964–2001. Data on R&D Personnel are from the NSF and cover the years 1964–1997.

Table 3 Tests for cointegration between employees, establishments, and R&D personnel

Test	Null: Variables	No cointegrating vector Likelihood ratio	At most one likelihood ratio
1	Employees and establishments	7.53	0.022
2	R&D personnel and establishments	8.49	0.007
3	Employees and R&D personnel	4.09	0.015

The null hypothesis is no cointegrating vector. The tests use the trace statistic test and the critical values for the null of no cointegrating vector are 13.33 for the 10% level, 15.41 for the 5% level, and 20.04 for the 1% level. For the null of at most one cointegrating vector the critical values are 3.76 for the 5% level and 6.65 for the 1% level. Results using the max eigenvalue statistic are largely the same

Data and Sources: Employees and establishments are from the County Business Patterns data and cover the years 1964–2001. Data on R&D Personnel are from the NSF and cover the years 1964–1997.

test for level stationarity (see Kwaitkowski, Phillips, Schimdt, & Shin, 1992), yields test statistics of 0.119 and 0.151, for employees and R&D workers per establishment respectively, using the maximum lags chosen by the Schwert criterion of nine. The critical value at the 10% level for rejection in both cases is 0.347.

We also tested for cointegration among employees, establishments, and R&D workers. Cointegration would suggest that the series are growing together at the same rate. Table 3 provides the results of three different possibilities using the Johansen Cointegration test. In none of the cases, can the null hypotheses of no cointegrating relationship or at most one cointegrating relationship between the variables be rejected at the 5% level. However, the time series is fairly short for these tests. So while we cannot reject no cointegrating vector, we also cannot reject that one exists.

To summarize, the evidence is quite strong that average establishment size and R&D workers per establishment are stationary, trendless variables unlike the level of employees and R&D workers. We now turn to the relationship between average establishment size and growth.

4.2 Is average firm size positively related to growth?

The R&D based growth models discussed above predict that an increase in average size leads to a temporary increase in the growth rate as firms move down their average cost curves. Over time, entry draws labor away from incumbent firms and the economy returns to equilibrium at the original growth rate.

Using the same time series tests as in Jones (1995a) we examine the question of interest.[7] The estimation technique takes the following form:[8]

$$g_t = A(L)g_{t-1} + B(1)X_t + C(L)\Delta X_t + \epsilon_t \tag{13}$$

$$c_k = -\sum_{i=k+1}^{p} b_i, \quad \text{where } k = 1, ..., p-1.$$

g_t is a measure of growth. Below we use both productivity growth and real per capita GDP growth as dependent variables. By writing the estimation in this manner, we can test directly the significance of the long-run effect of our independent variables X_t. $A(L)$ is a distributed lag and $B(1)$ captures the long-run effect of a change in the independent variable. Since it is not clear how long it will take growth to respond to changes in the independent variables, and the theories provide little in the way of predicting the timing of the impact of changes, we avoid imposing a strong interpretation on the individual lags. To determine the number of lags, we employ the Schwartz Information Criterion (SIC).[9] $C(L)$ is comprised of the distributed lagged coefficients on the differences in the X_t's, given by the expression for c_k.

For independent variables, the X_t's in (13), we use those suggested by the three versions of growth theory reviewed in the previous sections. First, we use aggregate levels of resources, both employment and R&D workers as implied by the first generation endogenous growth models. Next we use the growth rates in employment and R&D workers for the semi-endogenous growth models. Then, we use employment and R&D workers per establishment which emerges in the newer firm-based endogenous growth theories.[10] The test of the theories boils down to whether $B(1) > 0$.

Table 4 shows the specifications preferred by the SIC when using private business productivity growth as the dependent variable with the independent variable being the level of employment in the first column, the growth rate of employment in the second, and employment per establishment in the final column. Table 5 shows the same specification but using the growth rate of per capita GDP as the dependent

[7] That paper found changes in the investment share of GDP had no significant impact on growth rates, and negative in at least some cases, contrary to the predictions of AK models (e.g. Romer 1990).

[8] The derivation of this specification is presented in the technical appendix for clarification.

[9] The SIC is more efficient than other specification tests. However, Geweke and Messe (1981) show that in small samples, the SIC tends to predict too few lags. A technical appendix, available on request, shows the estimates after adding 1 and 2 additional lags respectively. None of the key results are changed when considering alternative specifications.

[10] One potential drawback of this approach is the possibility of reverse causality. It could be that employment, the growth rate of employment, or establishment size increases in anticipation of higher economic growth rates. However, for the average size variables, Pagano and Schivardi (2003) use a cross-country regression and explicitly test for reverse causality using an instrumental variable approach, but find no evidence for it. Their data utilize cross-country variation in employment shares across industrial sectors in a way that cannot be done here. However, their results suggest that the direction of causality runs from firm size to GDP growth rates, which lends additional support to the theories and the results described here.

Table 4 Productivity growth and employment

Dependent variable	Productivity growth		
Independent variable	Employment	Employment growth rate	Employment per establishment
Coefficient	0.000194	−0.0300	0.000564
T-statistic	4.055***	−0.316	2.551**
P-value	0.0003	0.754	0.0156
Lags	1	1	2
SIC	−5.280	−5.023	−5.049
No. of obs.	36	35	35

Notes: Data cover the years 1964–2001. All regressions performed with one lag of dependent variable. Coefficient and test statistics refer to B(1) in Eq. (13). Lags refers to the number of differenced lags, *P*, corresponding to C(L) in Eq. (13). Number of Observations varies due to loss of one through calculating growth rates or differences in lag number. Lag number determined by Schwarz Information Criterion. * Indicates significant at 10% level; ** 5% level; and *** 1% level

Table 5 GDP per capita growth and employment

Dependent variable	GDP per capita growth		
Independent variable	Employment	Employment growth rate	Employment per establishment
Coefficient	0.000253	−0.3240	0.00111
T-Statistic	4.165***	−1.808*	3.478***
P-value	0.0002	0.08	0.0015
Lags	1	1	2
SIC	−4.830	−4.563	−4.697
No. of Obs.	36	35	35

Notes: Data cover the years 1964–2001. All regressions performed with one lag of dependent variable. Coefficient and test statistics refer to B(1) in Eq. (13). Lags refers to the number of differenced lags, *P*, corresponding to C(L) in Eq. (13). Number of Observations varies due to loss of one through calculating growth rates or differences in lag number. Lag number determined by Schwarz Information Criterion. * Indicates significant at 10% level; ** 5% level; and *** 1% level

variable.[11] The SIC selects one lag only for the level and growth rate of employment, but two for employment per establishment in both sets of tests.

In both cases the *level* of employment is positively related to growth and highly significant at the 1% level. However, these results follow from the fact that productivity growth, while fluctuating considerably, was higher in the 1990s when employment was at its highest. Much of the higher growth rates in productivity coincide with high levels of employment. Figure 11 shows the employment level against a Hodrick–Prescott filtered version of the productivity growth rate.[12] The productivity growth rate displays a U-shaped pattern and thus for much of the sample, productivity is higher and rising from about 1980 onwards while employment is obviously growing over more or less the entire period as shown previously in Fig. 2. (See Ha and Howitt 2006 for a detailed discussion of the implications of this feature for testing growth theories.)

11 Per capita growth rates are from the US Bureau of Economic Analysis.

12 The Hodrick–Prescott filtered series use a band parameter of $\lambda = 100$ which is standard for annual data.

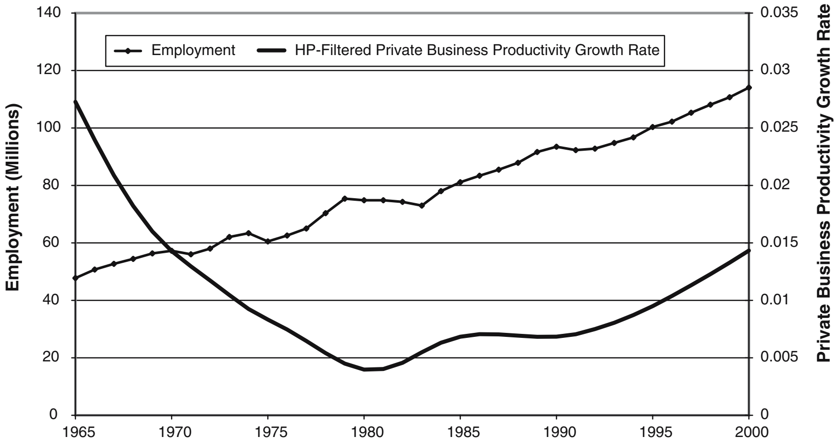

Fig. 11 Employment and HP Filtered Private Business Productivity Growth

The growth *rate* in employment, however, exhibits a negative relationship with economic growth and significantly so when using per capita GDP. This finding stands in contrast to the semi-endogenous growth model predictions. So, why should an increase in the growth rate of employment lead to a fall in the growth rate of productivity or real per capita GDP? To answer that we turn to the implications of the firm-based theories. First, employment per establishment is highly significant and positively related to both growth measures. But the transitional dynamics explain the previous results (see, e.g., Peretto, 1998; Peretto & Smulders, 2002). Greater size leads to higher productivity and output per product line, but it also induces entry. As firms enter, employment expands leading to higher levels of the employment growth rate. As entry occurs, wages are bid upwards and the mean size of establishments falls leading to lower productivity growth in the future.

Tables 6 and 7 show the same tests but using input measures based on R&D workers. The first column shows the effect of the level of R&D workers, the second shows the growth rate of R&D workers, the third shows the effect of R&D workers per establishment, and the final column uses the share of R&D workers in total employment which is typically assumed constant in the theoretical models.

The level of R&D personnel remains positive and significant though only at the 10% level now. The growth rate in R&D personnel switches signs and is significant at the 10% level when the dependent variable is GDP per capita growth. R&D personnel per establishment is significant at the 5% level. The SIC continues to select only one lag for all variables with the exception of R&D personnel per establishment. The share of R&D personnel in total employment is also positively and significantly related to both growth measures. That is reassuring as all the theories would predict that relationship. However, the theories that focus on the product line as the locus of innovation suggest that the share in employment is merely a proxy for average R&D employment per productive unit. With stable, trendless average size subjected to exogenous shocks fluctuations in the share variable reflect adjustment along both the intensive and extensive margins. These dynamics generate a stable long-run growth rate of productivity and hence the economy.

Table 6 Productivity growth and R&D personnel

Dependent variable	Productivity growth			
Independent variable	R&D personnel	R&D personnel growth rate	R&D personnel per establishment	R&D personnel share of employment
Coefficient	0.0139	0.0947	0.0536	0.867
T-Statistic	1.94*	0.882	2.236**	2.369**
P-value	0.0619	0.385	0.034	0.025
Lags	1	1	2	1
SIC	−4.953	−4.805	−4.984	−5.033
No. of Obs.	33	31	31	32

Notes: Data cover the years 1964–1997. All regressions performed with one lag of dependent variable. Coefficient and test statistics refer to B(1) in Eq. (13). Lags refers to the number of differenced lags, *P*, corresponding to C(L) in Eq. (13). Number of Observations varies due to loss of one through calculating growth rates or differences in lag number. Lag number determined by Schwarz Information Criterion. * Indicates significant at 10% level; ** 5% level; and *** 1% level

Table 7 GDP per capita growth and R&D personnel

Dependent Variable	GDP per Capita Growth			
Independent Variable	R&D Personnel	R&D Personnel Growth Rate	R&D Personnel per Establishment	R&D Personnel Share of Employment
Coefficient	0.0187	0.2790	0.112	1.439
T-Statistic	1.987*	1.823*	2.983***	2.567**
P-value	0.0561	0.079	0.0057	0.016
Lags	1	1	1	1
SIC	−4.511	−4.347	−4.551	−4.694
No. of Obs.	33	31	32	32

Notes: Data cover the years 1964–1997. All regressions performed with one lag of dependent variable. Coefficient and test statistics refer to B(1) in Eq. (13). Lags refers to the number of differenced lags, *P*, corresponding to C(L) in Eq. (13). Number of Observations varies due to loss of one through calculating growth rates or differences in lag number. Lag number determined by Schwarz Information Criterion. * Indicates significant at 10% level; ** 5% level; and *** 1% level

To put the coefficients related to establishment size in perspective, a doubling of workers per establishment (from the mean of the sample, approximately 15.1) leads to a 0.85 percentage point increase in productivity growth and a 1.67 percentage point increase in GDP per capita growth. A doubling of R&D workers per establishment evaluated at the mean, leads to an increase of 0.77 percentage points in productivity growth and a 1.63 percentage point increase in GDP per capita growth. More plausibly, the change from the lowest level to the highest level of workers per establishment observed in the data amounts to three workers per establishment which would increase productivity growth by 0.20 percentage points and GDP per capita growth by 0.33 percentage points. The same for R&D workers per establishment, a difference of about 0.04 R&D workers per establishment, implies an increase of 0.21 and 0.43 percentage points for productivity and GDP per capita growth, respectively.

Thus, time-series data for the US exhibit a positive and significant relationship between average establishment size, R&D workers per establishment and growth in productivity and GDP per capita.[13] This provides the strongest evidence to date in support of the recent vintage of endogenous growth models based on the interaction between the vertical (quality/productivity) and horizontal (variety) dimensions of technological change.

We leave it to future research to investigate stronger tests of the hypothesis that larger firm or establishment size is associated with higher growth rates. The major limitation to such studies is lack of available data. As mentioned above, Pagano and Schivardi (2003) looking at European data for the early 1990s and find a positive relationship between firm size and growth in a cross-country, cross-industry analysis. However, they fix the size distribution at one point in time and are unable to explore how changes in average size affect growth over time. The evidence here, however, does suggest that changes in the average size are positively correlated with productivity and per capita growth rates.

5 Conclusions

In this paper, we showed that the predictions of the recent vintage of models of long-run growth that rely upon firm-based knowledge accumulation are consistent with the data. First, we do not find time trends for either employees or R&D workers per establishment. Second, we find that average establishment size is positively and significantly related to growth.

While the data and the econometric tests presented here are consistent with the available firm-based theories, further evidence is called for. The main limitation of our evidence is that time-series data covering the variables of interest is available only for the United States. Future work, along the lines of Pagano and Schivardi (2003) and Porter and Stern (2000) should include examining the behavior of average firm and establishment size across countries for a longer time horizon.

If the evidence presented here withstands more rigorous testing, it suggests that our understanding of the sources of growth and of policies that might raise standards of living would benefit from paying greater attention to the modeling of R&D-performing firms and of the environment in which they make decisions. The models of firm-based knowledge accumulation that we discussed focus on the first moment of the firm size distribution, i.e., average firm size. Looking at higher moments of the firm size distribution appears to be a fruitful avenue for further theoretical exploration. Recent work by Klette and Kortum (2004), Thompson (2001), Aghion, Harris, Howitt, and Vickers (2001), and Laincz (2005) moves in that direction.

We believe that our evidence also suggests that much of the debate of the last 10 years regarding the scale effects has been misplaced. The criticism of the early models is important not because the assumption of constant returns to scale in the knowledge production function is empirically flawed, but because the level of aggregation of those models led directly to emphasizing particular policy variables (those

[13] Additional work, available in a technical appendix upon request, provides some alternative specifications to correct for two potential problems with the data. First, the data on employees and establishments is collected in March and the growth variables are end of the year. Hence, the first lag is not a full year. To check that we are not introducing endogeneity, we re-run the specifications, but using one lag further back. Second, the data for researchers is also end of the year, but the denominator, establishments, corresponds to the preceeding March. To account for this data mismatch, adjusted rd_t uses the R&D workers aggregate numbers from the previous year, such that the timing gap is only 3 months as opposed to nine. Neither of these modifications alter the results in any significant way.

that affect aggregate market size) over more plausible alternatives. The scale-effect critique spurred the development of alternative models based on more solid micro-foundations with different policy conclusions. We contend that these models are more plausible not just because they lack scale effects, but because they identify correctly the empirically relevant unit of analysis, i.e., they focus on the firm (product line) as opposed to the whole economy.

In our view, the policy invariance conclusion of semi-endogenous growth models concedes defeat in the quest for policies that promote growth. We see no reason to give up on endogenous growth theory when we have hardly begun to explore empirically all the variants of the endogenous growth hypothesis. The focus of the debate, therefore, should be redirected from the properties of the aggregate knowledge production function itself to the efficacy and welfare implications of the array of alternative policies suggested by the models. The problem with the simple models of endogenous growth formulated in the early stages of the research program is not that they mistakenly assumed linearity in the knowledge production function, it is that they ignored the disaggregated, local nature of the innovation process. Thus, the real challenge facing the field of economic growth is to develop plausible models with clearly testable hypotheses and gather the *disaggregated* data necessary to perform those tests.

6 Data appendix

Data on the number of establishments and employees for the United States was gathered from County Business Patterns various years. An establishment is defined as a "single physical location at which business is conducted or services or industrial operations are performed." They exclude self-employed persons, employees of private households, railroad employees, agricultural production workers, and most government employees (but do include those working in wholesale or retail liquor establishments, Federally-chartered savings institutions and credit unions, and hospitals).

We use the Bureau of Labor Statistics measure of Private Business Productivity with a base year of 1996. US GDP growth is from Bureau of Economic Analysis website.

Cross-country firm level data was obtained from the OECD website from the "Firm-Level Project." There is a missing observation for the UK in 1992. Note also that the data show a sudden spike for the US in 1992 in terms of employment and employment per firm. The data reported imply an increase in employment of 24.6% from 1991 to 1992 followed by a fall in employment of 18.0%. Clearly, 1992 data must be entered incorrectly.

The number of enterprises and employment are from the Small Business Administration and the US Census Bureau's Enterprise Statistics.

Total Number of R&D personnel from 1950 to 1988 was taken from Charles I. Jones website and the remaining data for 1989–1997 was collected from the National Science Foundation website.

The data on international growth and population is from the Penn World Tables 6.1. The countries used in Fig. 1 include: Argentina, Australia, Austria, Burundi, Belgium, Benin, Burkina Faso, Bangladesh, Bolivia, Brazil, Barbados, Botswana, Canada, Switzerland, Chile, China, Cote d'Ivoire, Cameroon, Republic of Congo, Colombia, Comoros, Cape Verde, Costa Rica, Denmark, Dominican Republic, Algeria, Ecuador, Egypt, Spain, Ethiopia, Finland, France, Gabon, United Kingdom, Ghana, Guinea, The Gambia, Guinea-Bissau, Equatorial Guinea, Greece, Guatemala, Guyana, Hong Kong, Honduras, Indonesia, India, Ireland, Iran, Israel, Iceland, Italy, Jamaica, Jordan, Japan, Kenya, Republic of Korea, Sri Lanka, Lesotho, Luxembourg, Morocco, Madagascar, Mexico, Mali, Mozambique, Mauritania, Mauritius, Malawi, Malaysia, Namibia, Niger, Nigeria, Nicaragua, Netherlands, Norway, Nepal, New Zealand, Pakistan, Panama, Philippines, Papua New Guinea, Portugal, Paraguay, Romania, Rwanda, Senegal, Singapore, Sierra Leone, El Salvador, Sweden, Swaziland, Seychelles, Syria, Chad, Togo, Thailand, Trinidad & Tobago, Turkey, Tanzania, Uganda, Uruguay, USA, Venezuela, South Africa, Zimbabwe, and Zambia.

Acknowledgements The excellent research assistance of Wagish Bhartiya and Urmila Dighe is gratefully acknowledged. We thank seminar participants at Duke University, Drexel University, the LACEA conference, 2003 held in Puebla, Mexico, the DEGIT IX conference, 2004 held in Reykjavik, Iceland, C. Alan Bester, Michelle Connolly, Maxym Dedov, Elias Dinopoulos, Peter Howitt, Rolando Morales, Barbara Rossi, and Peter Thompson for helpful discussions and comments.

References

Adams, J., & Jaffe., A. (1996). Bounding the effects of R&D: An investigation using matched establishment-firm data. *RAND Journal of Economics, 27*, 700–721.
Aghion, P., & Howitt., P. (1992). A model of growth through creative destruction. *Econometrica, 60*, 323–351.
Aghion, P., & Howitt., P. (1998). *Endogenous growth theory*. Cambridge, MA: MIT Press.
Aghion, P., & Howitt., P. (2005). Growth with quality improving innovations: An integrated framework. In P. Aghion & S. Durlauf (Eds.), *Handbook of economic growth*. Amsterdam: North Holland.
Aghion, P., Harris, C., Howitt, P., & Vickers, J. (2001). Competition, imitation, and growth with step-by-step innovation. *Review of Economic Studies, 68*, 467–492.
Backus, D., Kehoe, P., & Kehoe, T. (1992). In search of scale effects in trade and growth. *Journal of Economic Theory, 58*, 377–409.
Barro, R., & Sala-i-Martin, X. (2004). *Economic growth*. Cambridge, MA: MIT Press.
Ben-David, D., & Papell, D. (1995). The great wars, the great crash, and steady state growth: Some new evidence about an old stylized fact. *Journal of Monetary Economics, 36*, 453–475.
Broda, C., & Weinstein, D. (2006). Globalization and the gains from variety. *Quarterly Journal of Economics, 121*, 541–585.
Cohen, W., & Klepper, S. (1996). A Reprise of Size and R&D. *The Economic Journal, 106*, 925–951.
Dinopoulos, E., & Thompson, P. (1998). Schumpeterian growth without scale effects. *Journal of Economic Growth, 3*, 313–335.
Dinopoulos, E., & Thompson, P. (1999). Scale effects in schumpeterian models of economic growth. *Journal of Evolutionary Economics, 9*, 157–185.
Dunne, T., Roberts, M. J., & Samuelson, L. (1988). Patterns of Entry and Exit in U.S. Manufacturing Industries. *RAND Journal of Economics, 19*, 495–515.
Feenstra, R. C. (1994). New product varieties and the measurement of international prices. *American Economic Review, 84*, 157–177.
Galor, O. (2005). From stagnation to growth: Unified growth theory. In P. Aghion, & S. Durlauf (Eds.), *Handbook of economic growth*. Amsterdam: North Holland.
Geweke, J., & Meese, R. (1981). Estimating regression models of finite but unknown order. *International Economic Review, 22*, 55–70.
Grossman, G. M., & Helpman, E. (1991). *Innovation and growth in the global economy*. Cambridge, MA: MIT Press.
Ha, J., & Howitt, P. (2006) Accounting for trends in productivity and R&D: A schumpeterian critique of semi-endogenous growth theory. *Journal of Money, Credit, and Banking*(forthcoming).
Heston, A., Summers, R., & Aten, B. (2001). Penn world table version 6.1, Center for International Comparisons at the University of Pennsylvania (CICUP).

Howitt, P. (1999). Steady endogenous growth with population and R&D inputs growing. *Journal of Political Economy, 107*, 715–730.

Jones, C. I. (1995a). Time series tests of endogenous growth models. *Quarterly Journal of Economics, 110*, 495–525.

Jones, C. I. (1995b). R&D-based models of endogenous growth. *Journal of Political Economy, 103*, 759–784.

Jones, C. I. (1999). Growth: With or without scale effects? *Papers and Proceedings of the One Hundred Eleventh Annual Meeting of the American Economic Association, 89*, 139–144.

Jones, C. I. (2005). Growth and ideas. In P. Aghion & S. Durlauf (Eds.), *Handbook of economic growth*. Amsterdam: North Holland.

Kelley, A. C., & Schmidt, R. (2003). Economic and demographic change: a synthesis of models, findings, and perspectives. In N., Birdsall, A. C. Kelley, & S. Sinding (Eds.), *Population matters—demographic change, economic growth, and poverty in the developing world*. New York: Oxford University Press.

Klenow, P., & Bils, M. (2001). The acceleration in variety growth. *American economic Review, 91*,274–280.

Klenow, P., & Rodríguez-Clare, A. (2005). Externalities and growth. In P. Aghion and S. Durlauf (Eds.) *Handbook of economic growth*. Amsterdam: North Holland.

Klette, T. J. & Kortum, S. (2004). Innovating firms and aggregate innovation. *Journal of Political Economy, 112*, 986–1018.

Kocherlakota, N., & Yi, K. (1997). Is there endogenous long-run growth? Evidence from the United States and the United Kingdom. *Journal of Money, Credit, and Banking, 29*, 235–262.

Kortum, S. (1997). Research, patenting, and technological change. *Econometrica, 65*, 1389–1419.

Kremer, M. (1993). Population growth and technological change: One million B.C. to 1990. *Quarterly Journal of Economics, 108*, 681–716.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic series have a unit root. *Journal of Econometrics, 54*, 159–178.

Laincz, C. (2005). Market structure and endogenous productivity growth: How do R&D subsidies affect market structure?" *Journal of Economic Dynamics and Control, 29*, 187–223.

Pagano, P., & Schivardi, F. (2003). Firm size distribution and growth. *Scandinavian Journal of Economics, 105*, 255–274.

Peretto, P. (1996). Sunk costs, market structure, and growth. *International Economic Review, 37*, 895–923.

Peretto, P. (1998). Technological change and population growth. *Journal of Economic Growth, 3*, 283–311.

Peretto, P. (1999). Cost reduction, entry, and the interdependence of market structure and economic growth. *Journal of Monetary Economics. 43*, 173–195.

Peretto, P. (2003). Fiscal policy and long-run growth in R&D-based models with endogenous market structure. *Journal of Economic Growth, 8*, 325–347.

Peretto, P., & Connolly, M., (2004). The manhattan metaphor. working paper, Duke University.

Peretto, P., & Smulders, S. (2002). Technological distance, growth, and scale effects. *The Economic Journal, 112*, 603–624.

Porter, M. & Stern, S. (2000). Measuring the "Ideas" production function: Evidence from international patent output. *NBER Working Paper #7891*.

Romer, P. (1986). Increasing returns and long-run growth. *Journal of Political Economy, 94*, 1002–1037.

Romer, P. (1990). Endogenous technological change. *Journal of Political Economy, 98*, S71–S102.

Segerstrom, P. (1998). Endogenous growth without scale effects. *American Economic Review, 88*, 1290–1310.

Smulders, S., & van de Klundert, T. (1995). Imperfect competition, concentration and growth with firm-specific R&D. *European Economic Review, 39*, 139–160.

Thompson, P. (2001). The microeconomic structure of R&D based models of economic growth. *Journal of Economic Growth, 6*, 263–283.

Young, A. (1998). Growth without scale effects. *Journal of Political Economy, 106*, 41–63.

Zachariadis, M. (2003). R&D, innovation, and technological progress: A test of the schumpeterian framework without scale effects. *Canadian Journal of Economics, 36*, 566–586.