
Munich Personal RePEc Archive

Technological policy and wage inequality

Guido Cozzi and Giammario Impullitti

University of Glasgow, IMT Lucca

2006

Online at http://mpra.ub.uni-muenchen.de/10140/
MPRA Paper No. 10140, posted 18. September 2008 09:31 UTC

Technological Policy and Wage Inequality

Guido Cozzi* Giammario Impullitti†

This version: October 2006

Abstract

In this paper we argue that government procurement policy played a role in stimulating the wave of innovation that hit the US economy in the 1980's, as well as the simultaneous increase in inequality and in education attainment. Since the early 1980's U.S. policy makers began targeting commercial innovations more directly and explicitly. We focus on the shift in the composition of public demand towards high-tech goods which, by increasing the market-size of innovative firms, functions as a de-facto innovation policy tool. We build a quality-ladders non-scale growth model with heterogeneous industries and endogenous supply of skills, and show both theoretically and empirically that increases in the technological content of public spending stimulates R&D, raises the wage of skilled workers and, at the same time, stimulates human capital accumulation. A calibrated version of the model suggests that government policy explains up to 32 percent of the observed increase in wage inequality in the period 1978-91.

JEL Classification: E62, H57, J31, 031, 032, 041.

Keywords: R&D-driven growth theory, government procurement, wage inequality, educational choice, technology policy.

*Guido Cozzi, *Department of Economics, University of Glasgow.* Email: g.cozzi@lbss.gla.ac.uk

†Giammario Impullitti, *Department of Economics European University Institute Florence and IMT Lucca.* Email: giammario.impullitti@iue.it

1 Introduction

This paper studies the effects of both demand and supply-side innovation policy tools on technical change and wage inequality. Government policy consists of incresing the technological composition of public procurement, the demand-side tool, and of subsidies to R&D, the supply-side tool. Technical change is endogenous and government action produces both a reduction in innovation costs and a market-size effect that increase the profitability of innovative firms, thus stimulating investments in innovation. As innovation is a skill-using activity, government policy increases the relative demand of skills and the skill-premium.

In the early 1980's we observe a substantial increase in government investment in high-tech sectors: investment in equipment and software (E&S), which was 20 percent of total government investment in 1980, climbs to about 40 percent in 1990 and to more than 50 percent in 2001. The composition of private investment also switched towards E&S but more than a decade later, catching up with the public trend in the 1990s. This suggests that government played an important role in providing producers of new investment goods with the appropriate market size. We argue that this change in the composition of public spending reallocated market-size from low-tech to high-tech industries, thus enlarging the market for more innovative products and stimulating innovation. Missing data on the technological content of other kinds of government expenditure, we resort to the available data on government investment composition as a sample for the true composition of total government procurement. Our analysis remarks that lthough government procurement is not an explicit policy tool, it works as 'de facto' innovation policy instrument.

The introduction of the Research and Experimentation tax credit in 1981 was explicitly targeted at stimulating commercial innovation. The credit was designed to stimulate company R&D over time by reducing its after-tax cost. Specifically, companies that qualified for the credit could deduct or subtract from corporate income taxes an amount that in the period 1981-2004 has been in the range of 20 to 25 percent of qualified research expenses above a base amount. The credit rate was initially set at 25 per cent of "incremental" research and development: incremental meant above the level of the previous year in 1981, and in the following years the increase was measured over the average R&D spending in the previous three years. The credit rate was also reduced to 20 per cent from 1982 onward. Although the credit rate has been pretty constant, its incremental feature generates a persistent incentive for private firms to

increase their R&D investment over time.

In this paper we introduce government spending and R&D subsidies in a neo-Schumpeterian growth framework with heterogeneous industries. The core theoretical part of the paper is related to the construction of a mechanism that links the composition of public spending to relative wages.The introduction of R&D subsidies is standard and is confined to the calibration exercise.

We build a version of the quality-ladders growth model with endogenous supply of skills (Dinopoulos and Segerstrom 1999). A new and key feature of the model is the introduction of heterogeneous industries. The economy is populated with a continuum of sectors with asymmetric innovation power; in the language of quality-ladders models this implies that each sector has a different quality-jump any time an innovation arrives. In this setting we introduce government policy, in the form of a public spending rule: the government can allocate its expenditure in manufactured goods using a continuum of different policy rules, from the extreme symmetric rule, each sector gets the same share of public spending, to an asymmetric rule, the sector with the highest quality jump gets the highest spending.

In our model high-tech sectors are those where innovation brings technological improvements, quality jumps, that are greater than average. There are two activities in the economy: manufacturing, carried out by a continuum of asymmetric firms, and innovation activity or production of ideas. We suppose unskilled labor is used exclusively in manufacturing and that ideas are produced using skilled labor. There are two basic mechanisms in the model that link government policy to wage inequality. First, as the government reallocates spending from low to high-tech sectors aggregate profits increase. Intuitively, higher quality jumps in high-tech sectors implies higher mark-ups and larger profits. Hence, a redistribution of public spending in favor of these sectors rises aggregate profits in the economy. This increase in total profits triggers, via inter-sector innovation arbitrage, an increase in the relative demand of skilled workers and in their relative wage. Second, we model a innovation cost-reducing policy in the form of a standard symmetric innovation subsidy that increases profits in all sectors at the same rate, thus producing a general incentive to innovate that raises the demand for skilled workers in all sectors of the economy.

Finally, there is a training choice in the model that endogenizes skills formation and, as a consequence, policy has also a positive effect on the relative supply of skilled workers. Therefore,

our model is able to match two basic stylized facts of the U.S. labor market in the 1980's and 1990's, the contemporary increase in the supply of skills and in the skill premium (see Acemoglu 2002a figure 1).

We adopt a broad interpretation of innovation, in order to include all those activities that are targeted to increase firms' profits. In our model workers performing innovative activities are those workers that, with their intellectual skills, contribute to give a firm a competitive advantage over the others. Therefore, we do not restrict our view to R&D activities. While R&D workers play an important role in innovation, they are not the only skilled workforce that a firm needs to beat its rivals: managerial and organizational activities, marketing, legal and financial services are all widely and increasingly used by modern corporations to compete in the marketplace.

This paper is related to the literature on skill-biased technical change (SBTC).[1] Like works in this line of research, we focus on the role of technical change in affecting the U.S. wage structure in recent decades. In our paper innovation is skill-biased by assumption, as in models of exogenous SBTC (i.e. Aghion, Howitt, Violante 2002, Caselli 1999, Galor and Moav 2000, Krusell, Ohanian, Rios-Rull, Violante 2000), but technical change is endogenous, as in models of endogenous SBTC (Acemoglu 1998 and 2002b, Kiley 1998).[2] We share with endogenous technology models the idea that innovation is profit-driven and that market-size is one key determinant of profitability. Like endogenous SBTC models, we explore the 'sources' of technical change, but while these works focus on the market-size effect produced by the increase in the relative supply of skills, in our paper the source of the market-size effect is government spending. Moreover, strictly speaking, our model is not a model of SBTC in the sense that innovation does not increase the productivity of skilled workers. In our framework, as in Dinopoulos and Segerstrom (1999), innovation is simply a skill-intensive activity and wage inequality increases with the size of this activity.

Our paper is related to the Dinopoulos and Segerstrom (1999) version of the quality-ladder growth model. With respect to this work, our contribution is the following: first, on the theory side, the introduction of asymmetric steady states allows government spending to affect innovation and the skill premium. This is not obtainable with a simple introduction of government

[1] For a review of this literature see Acemoglu (2002), Aghion (2002) and Hornstein, Krusell, and Violante (2005).

[2] Galor and Moav (2000) in section IV introduce endogenous technical change through human capital accumulation.

spending into the Dinopoulos and Segerstrom's symmetric framework. Second, while their application focus on trade liberalization as the source of technical change and wage inequality, we focus on the role of government policy. To our knowledge, this is the first attempt to assess the relevance of the policy channel in the debate on technical change and wage inequality in the U.S.

The paper is organized as follows. Section 2 presents the stylized facts on government policy and wage inequality. Section 3 sets up the model. Sections 4 and 5 derive the main results and explain the intuitions for the macroeconomic consequences of asymmetric steady states. Section 6 provides econometric evidence of the significance of the channel we highlight in this paper. In section 7 we perform a calibration exercise and test the model's predictions against the observed change in wage inequality. Section 8 provides remarks on the qualitative and quantitative predictions of the model. Section 9 concludes. The appendix contains the proofs of our model's propositions and a description of US tax credit policy.

2 Stylized facts

In this section we provide some background evidence on the two policy tools on which we focus in the model, public spending composition and R&D subsidies, and on their relation with innovation and wage inequality. We postpone a formal econometric and calibration analyses to Sections 6 and 7.

2.1 Government spending composition and wage inequality: main features

The first set of facts that we analyze is related to the dynamics of public investment composition - the only available proxy for public procurement technological composition - and wage inequality in the 1980s and 1990s. Although government procurement has never been an explicit policy tool it has always worked as a de facto relevant innovation policy instrument. David Hart presents the argument in the following way: "[public] R&D spending was typically accompanied by other measures that deserve at least as much credit for their technological payoffs. For instance, the Department of Defense (DOD) not only funded much of the physical science and engineering R&D that led to advances in semiconductors and computers, it also purchased a large fraction of products themselves, especially the most advanced products.

The DOD guaranteed that a market for electronics would exist, inducing private investment on a scale that would not have otherwise followed even the most promising research results" (Hart 1998 p.1). Public procurement guaranteed a market to innovative firms, especially in early stages of product development. There is evidence that the DOD, NASA and also other government agencies, such as the Department of Health, contributed to private innovation via demand-pull (Ruttan 2003, and Finkelstein 2003).

In this paper we will propose an aggregate measure of this demand-pull channel for innovation. More precisely, the market-size effect that we model in the next section will be driven by the composition of public investment. We use BEA NIPA data that break-up public investment between E&S and structures. E&S includes a group of investment goods that are considered more innovative than those included in structures, so we choose E&S as our high-tech aggregate.[3]

In figure 1 we report the evolution of the skill premium and of the composition of government investment spending - expressed as the ratio of government investment in E&S over total government investment. The relevant fact here is that both series jump onto a strongly increasing path in the late 1970s early 1980s. This common and contemporaneous trend change suggests that the shift towards high-tech public spending, which started around 1974 and radically accelerated around 1978, might have had an influence on rising inequality in the 1980s.[4]

[FIGURE 1 ABOUT HERE]

Figure 2 shows that both the composition of public and private investment progressively shifted towards E&S since the late 1970s. The figure also suggests that public investment led the way and private investment followed with a lag of about a decade. Comparing public and private investment in E&S we find that the yearly average growth rate of private investment is 9 percent while the growth rate of public investment is almost double, 16 percent in the period 1970-90; private spending catches up only in the 1990s. Finally, using the same data it is possible to show that in 1978 the ratio of public to private investment in the innovative aggregate is 13 percent, it increases during the 1980s to reach a peak of 26 percent in 1990,

[3]See supportive evidence in Cummins and Violante 2002, and Hobijn (2001b). We consider only investment spending because there is no aggregate data that keeps track of the technological composition of public consumption expenditures.

[4]We are not interested in explaining the decline in the skill premium observed in the 1970s. For this reason the weaker correlation between the two series in the 1970s does not affect our argument.

and then starts declining.[5]

[FIGURE 2 ABOUT HERE]

As R&D represents an important part of the innovation activity, figure 3 shows that, as it was the case for public spending composition, also the trend of private R&D/GDP becomes strongly increasing in the late 1970s - along with that of the skill premium.

[FIGURE 3 ABOUT HERE]

The R&D subsidy discussed above affects exclusively the incentives to invest in R&D, while the technological composition of government procurement affects the market-size of all kinds of innovation activities, of which R&D is a relevant but not the only component.

3 The model

3.1 Households

Households differ in their members' ability to become skilled workers, and the ability, θ, is uniformly distributed over the unit interval. Households have identical intertemporally additively separable and unit elastic preferences for an infinite set of consumption goods indexed by $\omega \in [0,1]$, and each is endowed with a unit of labor/study time endowment whose supply generates no disutility. Households choose their optimal consumption bundle for each date by solving the following optimization problem:

$$\max \int_0^\infty N_0 e^{-(\rho-n)t} \log u_\theta(t) dt \tag{1}$$

subject to

$$\log u_\theta(t) \equiv \int_0^1 \log \left[\sum_{j=0}^{j^{\max}(\omega,t)} \lambda_\omega^j q_\theta(j,\omega,t) \right] d\omega$$

$$c_\theta(t) \equiv \int_0^1 \left[\sum_{j=0}^{j^{\max}(\omega,t)} p(j,\omega,t) q_\theta(j,\omega,t) \right] d\omega$$

$$W_\theta(0) + Z_\theta(0) - \int_0^\infty N_0 e^{-\int_0^t (r(\tau)-n)d\tau} T dt = \int_0^\infty N_0 e^{-\int_0^t (r(\tau)-n)d\tau} c_\theta(s) dt$$

[5] This indicates that the relative importance of public E&S is not negligible in the period of interest.

where N_0 is the initial population and n is its constant growth rate, ρ is the common rate of time preference - with $\rho > n$ - and $r(t)$ is the market interest rate. $q_\theta(j, \omega, t)$ is the per-member flow of good $\omega \in [0, 1]$ of quality $j \in \{0, 1, 2, ...\}$ purchased by a household of ability $\theta \in (0, 1)$ at time $t \geq 0$. $p(j, \omega, t)$ is the price of good ω of quality j at time t, $c_\theta(t)$ is nominal expenditure, and $W_\theta(0)$ and $Z_\theta(0)$ are human and non-human wealth levels. A new vintage of a good ω yields a quality equal to λ_ω times the quality of the previous vintage, with $\lambda_\omega > 1$. Different versions of the same good ω are regarded by consumers as perfect substitutes after adjusting for their quality ratios, and $j^{\max}(\omega, t)$ denotes the maximum quality in which the good ω is available at time t. As is common in quality ladders models we will assume price competition[6] at all dates, which implies that in equilibrium only the top quality product is produced and consumed in positive amounts. T is a per-capita lump-sum tax.

The instantaneous utility function has unitary elasticity of substitution and this implies that goods are perfect substitutes, once you account for quality. Thus, households maximize static utility by spreading their expenditures evenly across the product line and by purchasing in each line only the product with the lowest price per unit of quality, that is the product of quality $j = j^{\max}(\omega, t)$. Hence, the household's demand of each product is:

$$q_\theta(j, \omega, t) = \frac{c_\theta(t)}{p(j, \omega, t)} \quad \text{for } j = j^{\max}(\omega, t) \text{ and is zero otherwise} \tag{2}$$

The presence of a lump sum tax does not change the standard Euler equation:

$$\frac{\dot{c_\theta}}{c_\theta} = r(t) - \rho \tag{3}$$

Individuals are finitely lived members of infinitely lived households, being continuously born at rate β, and dying at rate δ, with $\beta - \delta = n > 0$; $D > 0$ denotes the exogenously given duration of their life[7]. People are altruistic in that they care about their household's total discounted utility according to the intertemporally additive functional shown in (1). They choose to train and become skilled, if at all, at the beginning of their lives, and the (positive) duration of their training period, during which the individual cannot work, has an exogenous duration $T < D$.

[6] All qualitative results maintain their validity under the opposite assumption of quantity competition.

[7] As in Dinopoulos and Segerstrom (1999, p.454) it is easy to show that the above parameters cannot be chosen independently, but that they must satisfy $\delta = \frac{n}{e^{nD}-1}$ and $\beta = \frac{ne^{nD}}{e^{nD}-1}$ in order for the number of births at time t to match the number of deaths at $t + D$.

Hence an individual with ability θ decides to train if and only if:

$$\int_t^{t+D} e^{-\int_t^s r(\tau)} w_L(s)ds < \int_{t+Tr}^{t+D} e^{-\int_t^s r(\tau)} \max(\theta-\gamma,0)\, w_H(s)ds,$$

with $0<\gamma<1/2$. The ability parameter is defined so that a person with ability $\theta>\gamma$ is able to accumulate skill (human capital) $\theta-\gamma$ after training, while a person with ability below this cut-off gains no human capital from training.

We will focus on the steady state analysis, in which all variables grow at constant rates and w_L, w_H, and c_θ are all constant. It easily follows that $r(t)=\rho$ at all dates, and that the individual will train if and only if her ability is higher than

$$\theta_0 = \left[\left(1-e^{-\rho D}\right)/\left(e^{-\rho Tr}-e^{-\rho D}\right)\right]\frac{w_L}{w_H}+\gamma \equiv \sigma\frac{w_L}{w_H}+\gamma. \tag{4}$$

The supply of unskilled labor at time t is

$$L(t)\equiv\theta_0 N(t)=\left(\sigma\frac{w_L}{w_H}+\gamma\right)N(t) \tag{5}$$

We set $w_L=1$, so the unskilled wage to be our numeraire. Following the same steps as Dinopoulos and Segerstrom (1999) the reader can easily verify that the supply of skilled labor at time s is

$$H(t)=(\theta_0+1-2\gamma)(1-\theta_0)\,\phi N(t)/2, \tag{6}$$

with $0<\phi=\left(e^{n(D-TR)}-1\right)/\left(e^{nD}-1\right)<1$. In steady state the growth rate of $L(t)$ and $H(t)$ is equal to n.

3.2 Manufacturing

Firms can hire unskilled workers to produce any consumption good $\omega\in[0,1]$ of the second best quality under a constant return to scale (CRS) technology with one worker producing one unit of product. However in each industry the top quality product can be manufactured only by the firm that has discovered it, whose rights are protected by a perfectly enforceable patent law. We will choose unskilled labor wage as the numeraire, that is: $w_L=1$.

As usual in Schumpeterian models with vertical innovation (see e.g. Grossman and Helpman 1991 and Aghion and Howitt 1998) the next quality of a given good is invented by means of innovation activity performed by challenger firms in order to earn monopoly profits that will be destroyed by the next innovator. During each temporary monopoly the patent holder can

sell the product at prices higher than the unit cost. We assume that the patent expires when further innovation occurs in the industry. Hence the monopolist rents are destroyed not only by obsolescence but also because a competitive fringe can copy the product using the same CRS technology.

The unit elastic demand structure[8] encourages the monopolist to set the highest possible price to maximize profits, but the existence of a competitive fringe sets a ceiling to it equal to the world lowest unit cost of the previous quality product. This allows us to conclude that the price $p\left(j^{\max}(\omega,t),\omega,t\right)$ of every top quality good is:

$$p\left(j^{\max}(\omega,t),\omega,t\right)=\lambda_{\omega}, \text{ for all } \omega\in[0,1] \text{ and } t\geq 0. \tag{7}$$

Here we introduce the crucial feature of the model: the government sector specific per-capita spending $G_{\omega}(t)\geq 0$, for all $\omega\in[0,1]$ and $t\geq 0$. The Government uses tax revenues to finance public spending in different sectors and we assume that the government budget is balanced at every date: $N(t)T(t)=N(t)\int_0^1 G_{\omega}(t)d\omega$. Moreover we will assume $N(t)T(t)<\gamma N(t)/a$, i.e. $T(t)<\gamma/a$, in order to guarantee that public expenditure is feasible. Since we will be interested in steady states, in which per-capita variables are constant, from now on we will drop time indexes from per-capita taxation and per-capita public expenditure.

>From the static consumer demand (2) we can immediately conclude that the demand for each product ω is:

$$\frac{N(t)\int_0^1 c_{\theta}d\theta}{\lambda_{\omega}}+\frac{N(t)G_{\omega}}{\lambda_{\omega}}\equiv\frac{cN(t)}{\lambda_{\omega}}+\frac{N(t)G_{\omega}}{\lambda_{\omega}}=q_{\omega}, \tag{8}$$

where $c=\int_0^1 c_{\theta}d\theta$ is average per-capita consumption. Sectoral market clearing conditions imply that demand equal production of every consumption good by the firm that monopolizes it, q_{ω}. It follows that the stream of monopoly profits accruing to the monopolist which produces a state-of-the-art quality product will be equal to:

$$\pi(\omega,t)=q_{\omega}\left(\lambda_{\omega}-1\right)=\left(cN(t)+G_{\omega}N(t)\right)\left(1-\frac{1}{\lambda_{\omega}}\right). \tag{9}$$

Hence a firm that produces good ω has an expected discounted value that satisfies

$$v(\omega,t)=\frac{\pi_{\omega}}{\rho+I(\omega,t)-\frac{\dot{v}(\omega,t)}{v(\omega,t)}}=\frac{q_{\omega}\left(\lambda_{\omega}-1\right)}{\rho+I(\omega,t)-\frac{\dot{v}(\omega,t)}{v(\omega,t)}},$$

[8] Any CES utility index with elasticity of substitution not greater than one would imply this result.

where $I(\omega,t)$ denotes the worldwide Poisson arrival rate of an innovation that will destroy the monopolist's profits in industry ω. In a steady state where per-capita variables all grow at the same rate, it is easy to prove that $\frac{\dot{v}(\omega,t)}{v(\omega,t)} = n$. Hence the expected value of a firm becomes

$$v(\omega,t) = \frac{q_\omega\left(\lambda_\omega - 1\right)}{\rho + I(\omega,t) - n}. \tag{10}$$

3.3 Innovation races

In each industry the leaders are challenged by the innovation activity of the followers that employ skilled workers and produce a probability intensity of inventing the next version of their products. The arrival rate of innovation in industry ω at time t is $I(\omega,t)$, and it is the aggregate summation of the Poisson arrival rate of innovation produced by all R&D firms targeting product ω.

In each sector new ideas are introduced according to a Poisson arrival rate of innovation by use of a CRS technology characterized by the unit cost function $bw_H X(\omega,t)$, with $b > 0$ common in all industries, and $X(\omega,t) > 0$ measuring the difficulty of innovation in industry ω. Hence the production of ideas is formally equivalent to buying a lottery ticket that confers to its owner the exclusive right to the corresponding innovation profits, with the aggregate rate of innovation proportional to the "number of tickets" purchased. The Poisson specification of the innovative process implies that the individual contribution to innovation by each skilled labor unit gives an independent (additive) contribution to the aggregate instantaneous probability of innovation: hence innovation productivity is the same if each skilled worker undertakes its activity by working alone as when she works with others in large firms.

The technological complexity index $X(\omega,t)$ has been introduced into endogenous growth theory after Charles Jones' (1995) empirical criticism of R&D based growth models generating scale effects in the steady state per-capita growth rate. According to Segerstrom's (1998) interpretation of Jones' (1995) solution to the "strong scale effect" problem (Jones 2005), $X(\omega,t)$ is increasing in the accumulated stock of effective innovation:

$$\frac{\dot{X}(\omega,t)}{X(\omega,t)} = \mu I(\omega,t), \tag{TEG}$$

with positive μ, thus formalizing the idea that early discoveries fish out the easier inventions first, leaving the most difficult ones for the future. This formulation implies that increasing

difficulty of innovation causes per-capita GDP growth to vanish over time unless an ever-increasing share of resources are invested in innovation, thereby requiring a growing educated population.[9] In the present framework with quality improving consumer goods "growth" is interpreted as the increase over time of the representative consumer utility level.

For industries targeted by innovation the constant returns to innovation activity and free entry and exit imply the no arbitrage condition

$$v(\omega,t) \equiv \frac{q_\omega\left(\lambda_\omega - 1\right)}{\rho + I(\omega,t) - n} = bw_H X(\omega,t). \tag{11}$$

The usual Arrow or replacement effect (Aghion and Howitt 1992) implies that the monopolist does not find it profitable to undertake any innovation activity at the equilibrium wages.

4 Balanced growth paths

We are now in a position to analyze the general equilibrium implications of the previous setting. Since each final good monopolist employs unskilled labor to manufacture each commodity, the unskilled labor market equilibrium is

$$N(t)\theta_0 = \int_0^1 q_\omega d\omega = \int_0^1 N(t)\left(\frac{c}{\lambda_\omega} + \frac{G_\omega}{\lambda_\omega}\right)d\omega = N(t)\left[\Gamma c + \Omega\right]. \tag{12}$$

Therefore:

$$c = \frac{\theta_0 - \Omega}{\Gamma}, \tag{13}$$

where $\Gamma = \int_0^1 \frac{1}{\lambda_\omega} d\omega$ and $\Omega = \int_0^1 \frac{G_\omega}{\lambda_\omega} d\omega$. Eq.s (8), (10), and (11) imply that

$$\frac{N(t)}{\lambda_\omega}\left(c + G_\omega\right) = bw_H X_\omega \frac{\rho + I_\omega - n}{\left(\lambda_\omega - 1\right)}, \tag{14}$$

which - since $w_H = \frac{\sigma}{\theta_0 - \gamma}$ and (13) holds - can be rewritten as:

$$\frac{1}{\lambda_\omega}\left(\frac{\theta_0 - \Omega}{\Gamma} + G_\omega\right) = \frac{b\sigma}{\theta_0 - \gamma} x_\omega \frac{\rho + I_\omega - n}{\lambda_\omega - 1}, \text{ for all } \omega \in [0,1], \tag{15}$$

where $x_\omega \equiv \frac{X_\omega}{N}$ denotes the population-adjusted degrees of complexity of product ω. Similarly, skilled labor market equilibrium implies:

$$\left(\theta_0 + 1 - 2\gamma\right)\left(1 - \theta_0\right)\phi/2 = b\int_0^1 I_\omega x_\omega d\omega. \tag{16}$$

[9] The acronym "TEG" refers to the "temporary effects on growth" of policy measures such as innovation subsidies and tariffs: they cannot alter the steady state per-capita growth rate, which is instead pinned down by the population growth rate. For this reason these type of frameworks are also called "semi-endogenous" growth models.

In steady state all per-capita variables are constant and therefore $\frac{\dot{X}(\omega,s)}{X(\omega,s)} = n$. Hence (TEG) implies: $I = n/\mu$. As usual in semi-endogenous growth models with increasing complexity the steady state arrival rate of innovation in every industry is a linear increasing function of the population growth rate. Hence we can rewrite (15) and (16) as follows:

$$\frac{1}{\lambda_\omega}\left(\frac{\theta_0 - \Omega}{\Gamma} + G_\omega\right) = \frac{b\sigma}{\theta_0 - \gamma} x_\omega \frac{\rho + n/\mu - n}{\lambda_\omega - 1}, \text{ for all } \omega \in [0,1], \tag{17}$$

$$(\theta_0 + 1 - 2\gamma)(1 - \theta_0)\phi/2 = b\frac{n}{\mu}\int_0^1 x_\omega d\omega \equiv b\frac{n}{\mu}\overline{x}. \tag{18}$$

Proposition 1 *If* $\frac{\Omega - \Gamma\overline{G}}{\Gamma} < \frac{(1-2\gamma)\phi\mu\sigma(\rho+n/\mu-n)}{2n\gamma}$ *a steady state always exists for every distribution of* $\lambda_\omega > 1$ *and* $G_\omega > 0$. *At each steady state the following properties hold:*

a. $G_\omega > G_{\omega'}$ *implies* $x_\omega > x_{\omega'}$ *and* $\partial x_\omega/\partial G_\omega > \partial x_{\omega'}/\partial G_{\omega'}$ *iff* $\lambda_\omega > \lambda_{\omega'}$

b. θ_0 *is an increasing function of* Ω

Proof. See the Appendix. ■

Proposition 1a suggests that an increases in government spending in a sector ω stimulates innovation in that specific sector through a market size effect - according to (TEG) the difficulty index x_ω is proportional to investment in innovation in sector ω. Moreover the proposition shows that 1 dollar of government spending is more effective in stimulating innovation when directed towards sectors with high quality jumps. The importance of proposition 1b will be more clear later, for the moment it suffices to notice that it shows that the share of unskilled workers θ_0 is increasing with the technology-adjusted average government spending Ω.[10]

5 Fiscal policy rules

Here we specify rules for public spending and derive the two basic results of the paper. The fiscal policy rule that we use is a linear combination of two extreme rules: a perfectly symmetric rule in which every sector gets the same share of public spending, that is $G_\omega = \overline{G}$, and a rule that allocates public spending in proportion to the quality jump in innovation, that is $G_\omega = \overline{G}\frac{\lambda_\omega}{\overline{\lambda}}$. Finally, the linear combination of the two extreme rules yields the general rule $G_\omega = (1-\alpha)\overline{G} + \alpha\overline{G}\left(\lambda_\omega/\overline{\lambda}\right)$, with $0 \leq \alpha \leq 1$.

[10] The average goverment spending is $\overline{G} = \int_0^1 G_\omega d\omega$.

Proposition 2 *Every move from a symmetric rule to a rule that promotes more the sectors with quality jumps above average, that is an increase in α, produces a decrease in Ω , which implies a decrease in the share of the population that decide not to acquireskills θ, and an increase in the skill-premium w_H.*

Proof. The general rule yields $\Omega = \overline{G}\left[\int_0^1 \frac{1-\alpha}{\lambda_\omega} d\omega + \frac{\alpha}{\overline{\lambda}}\right]$ and deriving Ω with respect to α we get $\partial\Omega/\partial\alpha = \overline{G}\left[-\int_0^1 \frac{1}{\lambda_\omega} d\omega + \frac{1}{\overline{\lambda}}\right]$: Jensen's inequality implies that $\partial\Omega/\partial\alpha < 0$. Thus, a shift to a more asymmetric spending (an increase in α) decreases Ω that, according to proposition 1.a, generate a decrease in the share of the population that decide not to acquire skills, θ_0. Recalling that the skill premium is $w_H = \sigma/(\theta_0 - \gamma)$ we conclude that an higher α leads to higher wage inequality. ■

Proposition 2 contains the basic result of the model: when government switches to a policy promoting high-tech sectors, as it has been the case in the US during the 1980's and 1990's, there is a decrease of the relative supply of unskilled workers and an increase of the skill premium. This theoretical result matches two stylized facts of the US labor market: the increase in the skill premium and the increase in the relative supply of skilled workers (see Acemoglu 2002a figure 1).

Propositions 2 contains results that are not attainable with the baseline Dinopoulos and Segerstrom model, and are directly related to our asymmetric-industry setting. In fact, the policy shift that we describe would not have any effect on the skill premium in a setting with symmetric steady states. One dollar of public money in high-tech yields more additional profits than those lost taking one dollar away from low-tech sectors - markups are larger in high-tech - and the net result is an increase in aggregate profits and innovation activity.[11] When sectors are symmetric the profit rate is the same in all industries and aggregate profits would not be affected by a reshuffling of government spending.

6 Econometric Analysis

In this section, we test statistically the direct and indirect mechanism highlighted in this paper: using established US data, we will look for a positive effect of government spending on innova-

[11] >From (9) we know that λ_ω coincides with the markup over the unit cost for the sector ω.

tion and the skill premium, via its positive effect on private R&D expenditure. The calibration exercise of the next section will provide a structural analysis of the quantitative effect of public spending on wage inequality.

With a first regression, we explore the effects of the composition of public spending on private investment in R&D, as a share of GDP, in the U.S. for the period 1953-2001. We find that public investment in E&S, as a share of total public investment, has a positive and substantial effect on private R&D.

TABLE I		
PUBLIC SPENDING COMPOSITION AND R&D INVESTMENT		
dependent variable: R&D/GDP		
regressors:	coeff	prob
GE&S/GI	0.295992	0.0487
R&D/GDP(-1)	0.951597	0.0000
n. of obs. adjusted	55	
R-squared	0.98449	
Adjusted R-squared	0.984111	
Breusch-Godfrey LM F stat	1.051945	prob = 0.407103
Breusch-Godfrey LM Obs*R-squared	6.511739	prob = 0.368366
Source: BEA, Nipa tables sections 5 and 7.		

The regression results reported in table show positive effects of government investment in E&S. Precisely, a 1 percentage point increase in the share of government E&S over total government investment rises current R&D over GDP by 0.29 percentage points. Notice that we have not used the constant as it was not significant even at 10%. Since there is a lagged dependent variable among the regressors the Durbin-Watson statistic - equal to 1.649982 - for serial correlation is not valid. Therefore we performed a Ljung-Box Q-statistics which rejects the null hypothesis of residuals autocorrelation. We also performed Breusch-Godfrey Lagrange multiplier tests[12], which rejects the null hypothesis of residuals serial correlation at all lags. Both explanatory variables, when subjected to an Augmented Dickey-Fuller (ADF) test do not prove stationary: they fit in the null hypothesis of a unit root. Therefore we performed an ADF test on the regression residuals. Fortunately the test statistics[13] is equal to -5.663348 which also passes the stricter Engle e Yoo's (1987) version of the unit root test. Therefore the

[12] One, with four lags, is reported in Table I.

[13] Mac Kinnon's test critical values are: 1% level , -2.615093; 5% level, -1.947975; 10% level, -1.612408.

regression is reliable.

We also looked at the what the data say about the relationship between non-federal R&D expenditure and skill premium. Here we have a shorter time series, 1963-1999, due to skill premium data (taken from Krusell et al., 2000) availability, but the results are good, as shown in the following table:

TABLE II		
R&D INVESTMENT AND SKILL PREMIUM		
dependent variable: skill premium		
regressors:	coeff	prob
R&D/GDP	0.047074	0.0388
skill premium(-1)	0.961224	0.0000
n. of obs. adjusted	36	
R-squared	0.914528	
Adjusted R-squared	0.912015	
Breusch-Godfrey LM F stat	1.213211	prob = 0.325839
Breusch-Godfrey LM Obs*R-squared	5.003754	prob = 0.286913
Source: BEA, Nipa tables sections 5 and 7.		

Also in this case the Durbin-Watson statistic - equal to 1.614102 - is invalidated by the presence of the lagged dependent variable among the regressors. Hence we performed Q-tests and LM tests[14], showing no serial correlation of residuals at all lags. Since non-stationary time series are involved also in this regression, we performed an ADF test on the regression residuals, obtaining statistic[15] value -5.505896, which also passes the stricter Engle e Yoo's (1987) version of the unit root test. This regression is therefore reliable too.

In light of the evidence reported in this section, we can say that the US data suggest the presence of:

- a positive and highly significant effect of the equipment and structure fraction of government investment on the private R&D/GDP ratio;
- a positive and highly significant effect of the private R&D/GDP ratio on the skilled wage/unskilled wage ratio.

We can now wonder how these two effects concur in a unique indirect effect of public investment composition on the skill premium. This is assessed by directly estimating this effect, as reported in the next regression:

[14] One, with four lags, is reported in Table I.

[15] Mac Kinnon's test critical values at 1% level of significance is -3.639407.

TABLE III		
PUBLIC SPENDING COMPOSITION AND SKILL PREMIUM		
dependent variable: skill premium		
regressors:	coeff	prob
GE&S/GI	0.137137	0.0388
skill premium(-1)	0.976489	0.0000
n. of obs. adjusted	36	
R-squared	0.917077	
Adjusted R-squared	0.914638	
Breusch-Godfrey LM F stat	1.373256	prob = 0.266687
Breusch-Godfrey LM Obs*R-squared	5.562143	prob = 0.234321
Source: BEA, Nipa tables sections 5 and 7.		

Also in this case the Durbin-Watson statistic - equal to 1.640411 - is invalidated by the presence of the lagged dependent variable among the regressors. Hence we performed Q-tests and LM tests[16], rejecting serial correlation of residuals at all lags. Since non-stationary time series are involved also in this regression, we performed an ADF test on the regression residuals, obtaining statistic[17] value -5.817913, which also passes the stricter Engle e Yoo's (1987) version of the unit root test. This regression is therefore reliable too.

7 Numerical analysis

In this section we calibrate a two-sector version of the model. All the results obtained for the model with a continuum of sectors hold for this shortcut version. The calibration allows an assessment of the quantitative effects of government policy on the skill premium. Since, as we saw in section 2, the only available data on public spending composition are those on investment, in the calibration exercise we need to reinterpret the model in terms of intermediate goods. As it is well know in the literature an alternative interpretation of quality ladders models is one where households consume a homogeneous consumption good which is assembled from differentiated intermediate goods. The static utility function in (1) can be then interpreted as a CRS production function where better quality intermediate goods are more productive in manufacturing the final good.[18]

[16] One, with four lags, is reported in Table I.

[17] Mac Kinnon's test critical values at 1% level of significance is -2.634731.

[18] See Grossman and Helpman (1991) ch. 4.

7.1 Calibration

The exercise consists of choosing the 8 parameters of the model $\{D, Tr, \rho, \gamma, n, \mu, \lambda_1, \lambda_2\}$ to match salient long-run features of the U.S. economy. Since we work with intermediate goods we need to choose our unit of time to be large enough to match the average life of intermediate goods. For this purpose we choose five years as our unit of time.[19] After calibrating the model we explore the effects of government policy on the skill premium between the two 5-years periods, 1976-80 and 1987-91.[20] We first compute the increase in the skill premium produced by shocking the model with the change in the composition of public spending showed in figure 1 and we compare it with the increase in the skill premium observed in the data. Later, we introduce the R&D subsidy and repeat the exercise for this policy shock.

The calibration of some parameters is standard. We set ρ, which in steady state is equal to the interest rate r, to 0.07 to match the average real return on the stock market for the past century of 7 percent, estimated in Mehra and Prescott (1985).[21] We calibrate n to match the population growth rate of 1.14%, as in Jones and Williams (2000). Since our time unit is 5 years both ρ and n must be multiplied by five, as we do in table II below. We choose the total working life time $D = 40$ as in Dinopoulos and Segerstrom (1999), and the total training time $Tr = 5$, to match the average years of college in the US - both values are adjusted for our time unit in table II.[22] We choose the threshold γ to bound the relative supply of unskilled workers above 75 percent of the workforce, as in Dinopoulos and Segerstrom (1999).

The crucial parameters of the calibration are the R&D difficulty index μ, and the quality jumps of the low and high-tech sectors, λ_1 and λ_2 respectively. We calibrate the quality jumps using estimates of the sectorial markups for 2-digit US manufacturing firms. We use Roeger (1995) estimates, which are the most conservative among the several others that we explored

[19] Since there is no capital in the model we consider intermediate goods as fully depreciating every period. Average full depreciation period of intermediate goods is 8-10 years. We choose the lenght of a period to be not greater of the average training time, which we assume to be 5 years.

[20] We choose 1976-80 as the starting year because it corresponds to the moment when the composition of public spending starts moving faster towards high-tech goods, and it is also very close to the turning point of the dynamics of the skill premium. The choice of 1987-1991 as second period is due to the fact that estimates for the effective R&D tax credit rate are available only up to 1991.

[21] Jones and Williams (2000) suggest that the interest rate in R&D-driven growth models is also the equilibrium rate of return to R&D, and so it cannot be simply calibrated to the risk-free rate on treasury bills - which is around 1%. They in fact calibrate their R&D-driven growth model with interest rates ranging from 0.04 to 0.14.

[22] Dinopoulos and Segerstrom (1999) use a training time of four years, we stretch it to five to match our time unit of five years.

both in the levels and sectorial differences. We use the revised OECD classification of high-tech and low-tech sectors as in Hatzichronoglu (1997)[23]. Specifically we take the lower bound of both high-tech and low-tech groups in Roeger's estimates, that is, we consider a 15 percent and 34 percent markups for low and high-tech respectively[24]. In the five-years time frame we are working with this imply setting $\lambda_1 = (1 + 0.15 * 5) = 1.75$ and $\lambda_2 = 1 + 0.34 * 5 = 2.7$.

Once we calibrated the two quality jumps we can use the equation for the growth rate to obtain the difficulty index parameter μ.

$$g = \frac{\dot{u}}{u} = I \int_0^1 \log \lambda_\omega d\omega = \frac{n}{\mu} \frac{1}{2} \left(\ln \lambda_1 + \ln \lambda_2 \right). \tag{19}$$

>From Penn World tables we get an average GDP growth rate for the period 1976-1991 in the U.S. of 2.3 percent and using the quality jumps, calibrated as explained above, we obtain μ equals to 0.067, which is the parameter of the R&D difficulty index[25].

To account for the real weight of public investment expenditure on the overall economy we introduce government investment as a share of total private investment.[26] Therefore we set $\beta_\omega = \frac{G_\omega}{c}$ and the demand (8) becomes:

$$\frac{cN(t)}{\lambda_\omega} + \frac{N(t)\beta_\omega c}{\lambda_\omega} = \frac{N(t)c}{\lambda_\omega}(1 + \beta_\omega) = q_\omega.$$

Working out the equilibrium with this modification and reducing the system to one equation - as we did in (A.1.1) - and substituting $w_H = \frac{\sigma}{\theta_0 - \gamma}$ into it we obtain a relation between the skill premium and the composition of public spending (share of low-tech goods $\frac{G_1}{c}$ and share of high-tech goods $\frac{G_2}{c}$):

[23] In our high-tech group we include sectors classified as high-tech and medium high-tech in Hatzichronoglu (1997), and similarly we contruct our low-tech group.

[24] We are aware of using different sector classifications for markups and for public investment. This is due to lack of estimates of markups for E&S and strucutures, and to lack of data on goverment procurement by industry. This simplification does not seem to be problematic because calibrating the markups using different growth rates for E&S and structures we would obtain a similar picture. In fact, calibrating μ externally we could use two separate growth equations, $g_1 = (n/\mu) \ln \lambda_1$ and $g_2 = (n/\mu) \ln \lambda_2$, and estimates of the growth rates in E&S and structure to calibrate λ_1 and λ_2. Cummins and Violante (2002) find that average technical change in E&S in the last 30 years in the U.S. to be between 5 and 6 percent. Gort, Greenwood and Rupert (1999) find a 1 percent yearly average structures-specific technical change in the last three decades. We performed this exercise and obtained similar calibrated values for the two quality jumps.

[25] We use equal weights for the two sectors for simplicity. We have also performed the exercise using some measure of the weights of the high-tech and low-tech sectors in the real economy and we get similar results. Morover, using similar weight seems more appropriate in a stylized model like ours where the R&D difficulty is common for both sectors.

[26] Private spending in the model, labeled c, is consumption. In the calibration, since we work with investment data, private spending is private investment.

$$\left(\frac{\sigma}{w_H}+1-\gamma\right)\left(1-\frac{\sigma}{w_H}+\gamma\right)\phi/2=\frac{n(\frac{\sigma}{w_H})}{\mu\sigma(\rho+n/\mu-n)}\left(\frac{\frac{\sigma}{w_H}+1}{\Gamma+\Psi}\right)\left(1-\Gamma+\overline{\beta}-\Psi\right), \quad (20)$$

where : $\overline{\beta}=\int_0^1\beta_\omega d_\omega=0.5*\frac{G_1}{c}+0.5*\frac{G_2}{c}$ and $\Psi=\int_0^1\frac{\beta_\omega}{\lambda_\omega}d_\omega=0.5*\frac{G_1}{\lambda_1 c}+0.5*\frac{G_2}{\lambda_2 c}$. Table IV below summarizes our parameters' calibration.

TABLE IV

SUMMARY OF CALIBRATION

parameter	value	moment to match	source
D	8	life time after college	Dinopoulos-Segerstrom 1999
T	1	years of college	Dinopoulos-Segerstrom 1999
ρ	0.15	interest rate	Jones and Williams (2000)
n	0.07	population growth rate	Jones and Williams (2000)
γ	0.75	low-bound for the share of unskilled workers	Dinopoulos-Segerstrom 1999
μ	0.43	GDP growth rate of 2.3%	Penn World Tables
λ_1	1.75	low-tech markup of 15%	Roeger (1995)
λ_2	2.7	high-tech markup of 34%	Roeger (1995)

For the policy variables on public spending we use BEA NIPA data on government investment in structure (G_1), our low-tech aggregate, and E&S (G_2), our high-tech aggregate[27]. NIPA data on public expenditure shows the following composition in the two periodsof interest: in 1976-80 average government investment in structure was 29 percent and in E&S sectors was 7 percent of total private investment ($\frac{G_1}{c}=0.29$ and $\frac{G_2}{c}=0.07$); in the period 1987-91 the low-tech expenditure share decreases to 26 percent and the high-tech share rises to 18 percent. This change in the composition of public spending in favor of high-tech sectors produces, in our calibrated model, a 2.1 percent increase in the skill premium. For the observed skill premium we use CPS data from Krusell, et al. (2000) on average wages of college graduates and high-school graduates. In the period considered this measure of the skill premium increased by 17.8 percent. Hence, our demand composition shock can explain 12 percent of the total increase in the skill premium showed in the data.[28]

[27]Notice that here we do not exactly use the fiscal policy rules specified in section 5. This is because when in this shortcut version of the model those rules would not allow us to catch the entire effect of a change in the composition of public spending on the skill premium. In fact, in the case of extreme asymmetric spending ($\alpha=1$) our rule predicts that the low-tech sector gets a share of the public spending that is proportional to it's quality jump. While, in the real world the extreme asymmetry would mean that the spending going to the low-tech sector would be zero ($G_1=0$). Thus, to keep the model closer to the real world in the calibration excercise we use directly government expenditure in the two sectors as an index of spending composition.

[28]The measure of inequality that we use, w_H/w_L, might overstate the increase in the skill premium when

In Table III below we study the sensitivity of the results to changes in the difference of the sectorial quality jumps, which is a proxy of the 'technology gap' between the two sets of industries. We leave λ_1 unchanged and increase λ_2 to match an average markup of 87 percent - the high-tech sector average in Roeger's estimates. We find that the percentage of the observed skill premium explained by the model improves with a higher 'technology gap'.

TABLE V

CHANGE IN THE SKILL PREMIUM EXPLAINED BY POLICY SHOCKS

	$\lambda_2 = 2.7$	$\lambda_2 = 5.35$
Spending Composition	0.12	0.25
Subsidy	0.20	0.20
Joint shock	0.32	0.46

Next, we introduce in the model a policy measure that reduces the cost of innovation in the form of a simple symmetric innovation subsidy. Innovation subsidies are funded with lump-sum taxes, in the same fashion as public spending, therefore government's balanced budget condition becomes $T(t) = \int_0^1 G_\omega(t)d\omega + s_r(t)$ - s is a subsidy to innovation equal for both sectors. It is easy to show, using household's intertemporal budget constraint, that the increase in subsidies does not crowd out private expenditure because additional taxes are returned to consumers in the form of higher profits. Therefore, subsidies increase profits symmetrically in all industries. This suggests that an increase in innovation subsidies rises aggregate profits and aggregate investment in innovation, thus increasing the skill premium. With R&D subsidies the equilibrium condition used for the calibration (20) changes in the following way:

$$\left(\frac{\sigma}{w_H} + 1 - \gamma\right)\left(1 - \frac{\sigma}{w_H} + \gamma\right)\phi/2 = \frac{n(\frac{\sigma}{w_H})}{(1-s)\,\mu\sigma(\rho + n/\mu - n)}\left(\frac{\theta_0}{\Gamma + \Psi}\right)\left(1 - \Gamma + \overline{\beta} - \Psi\right). \tag{21}$$

The data on the R&D subsidy implicit in the R&D Tax Credit are taken from Hall (1993) estimates that are, to date, the only that directly compute the effective credit rate. The annual across-sectors average credit rate varies between 3.04 percent in 1981 and 7.49 percent in 1991.

we bring the model to the data. The reason is that the average wage of skilled workers in the model is $\int_{\theta_0}^1 (\theta - \gamma) w_H dF(\theta)$ which is smaller than w_H. We do not use this measure in the calibration because there is a semplification in the model that counterbalances the overstatement of the skill premium generated by using w_H as average skilled wages. In fact we assumed that unskilled workers do not accumulate human capital, and so their average wage is simply w_L. In the data average wages of both skilled and unskilled are computed taking into account the 'abilities', or human capital, of heterogeneous workers in the two groups. So using w_L in the model for the average unskilled wage understates the real measure of the skill premium. Our take is to leave human capital accumulation out of the measure of inequality in the calibration to avoid distortions in both directions.

In our starting period, 1976-80 the credit is 0, since it was introduced in 1981, in the ending period, 1987-91, the average credit rate is estimated to be around 4 percent per year. It turns out that the introduction of the subsidy alone produces a 3.8 percent increase in the skill premium, accounting for about 20 percent of the real change in the skill premium over the period.

As we can see in table III, the incentive effect of an innovation subsidy is not very sensitive to changes in the 'technology gap'. This happens because although an increase in λ_2 raises the markup of high-tech firms, so stimulating innovation, it also raises the innovation difficulty index μ, as calibrated in (19), so worsening the incentives to innovate.

8 Discussion

We conclude this section with some remarks on the predictions of the model and on the quantitative results obtained in the calibration.

R&D expenditure and wage inequality. Even though R&D is not the sole innovation activity stimulated by our policy shocks it is an important part of it, and the model indirectly predicts a positive linkage between R&D expenditure and the skill-premium. Figure 3 shows a common shift in the trend of the private R&D share of GDP and of the skill premium in the late 1970s early 1980s. Machin and Van Reenen (1998), using industry-specific R&D intensity as an indicator of technology, find a strong correlation between technical change and skill upgrading in the U.S. in the 1980s[29]. More precisely, they find that both R&D intensity and the wage share of non-production workers grew in the 1980s, and that R&D intensity is a significative regressor for the wage and employment share of non-production workers in all manufacturing sectors. In addition to this they also show that while skill-upgrading is observed within all industries, it appears to be more intense in high-tech sectors.

Within and between-industry changes. In our model the demand-composition shock produces skill-upgrading in high-tech sectors and deskilling in low-tech sectors, while R&D subsidies increase the relative demand for skills in all sectors. The extent to which R&D subsidies compensate for the negative skill-upgrading in low-tech industries produced by government expenditures depends on the parameters of the model and on the relative strength of the two types

[29] Their analysis included also other OECD countries.

of policies. Hence, in principle, the model could predict skill-upgrading and increasing wage inequality in both high-tech and low-tech sectors, with higher intensity in the former group of industries -in accordance to the evidence in Machin and Van Reenen (1998). In the benchmark calibration the share of wage inequality attributable to our within-industry mechanism, triggered by the R&D subsidy, is about 20 per cent, while the between-industry mechanism, the demand composition shock, explains about 12 percent. There is consensus in the literature that most of the recent increase in wage inequality is explained by within-industry changes and that between-industry changes play a minor but non-negligible role. Berman, Bound and Griliches (1994), for instance, find that between-industry changes explain about one third of the total increase in the share of the wage bill of non production workers in the period 1979-87. Moreover, they find that the primary source of inequality induced by between-industry changes was explained by defense procurement.[30]

The recent empirical literature on sector-specific technical change confirms the idea that high-tech sectors have been the major engine of innovation in the last decades.[31] Cummins and Violante (2002) find that average technical change in E&S in the last 30 years in the U.S. to be between 5 and 6 percent. In this literature the change in E&S is proxied by the difference in growth rates between constant-quality consumption prices and quality-adjusted prices of investment in E&S. The substantial decline of the quality-adjusted price of capital equipment since the early 1970s provides evidence of E&S-specific technical change. Recently some empirical works have showed that, although technical change in structures is less relevant than that in equipment goods, it has been positive and significative in the last decades. Gort, Greenwood and Rupert (1999) find a 1 percent yearly average structures-specific technical change in the last three decades. In line with this evidence, the demand-pull effect of public spending composition reduces the quality-adjusted prices of high-tech goods more than those of low-tech goods.

R&D subsidies. Even though the incremental feature of the tax credit reduced its effective rate, as we explained in section 2, there is extensive evidence showing that it did have an impact on private innovation. Hall (1993) working on firm-level data finds that private innovation responds to reductions in the after-tax cost of R&D -often called the tax price of R&D. In her

[30] They rely on evidence that defense related industries tend to employ a large proportion of non production workers, especially with the emphasis put on high-tech weapons since the late 1970s (see also O'Hanlon, 2000).

[31] See Hornstein et al. (2005).

estimates the tax price elasticity of R&D is larger than one, which means that a 5 per cent effective R&D tax credit leads to a 5 percent average increase in R&D at the firm level. These findings are confirmed by those in Hines (1993) that uses different econometric methods, and by those in Baily and Lawrence (1992) based on macro data. Bloom, Griffith and Van Reenen (2002) find an elasticity around unity for a panel of countries including the U.S. in the period 1981-99.

Autonomous private innovation. We want to emphasize that our analysis is not meant to exclude or downplay any autonomous role of private innovation. Indeed, one could introduce asymmetry in private spending and study the effects of changes in its composition, showed in figure 2, on the wage structure. We expect that the shift in public spending composition will be relatively more relevant in the 1980s, and private spending composition will be the main factor in the 1990s. Moreover, changes in the economic environment, such as trade liberalization and increasing international technological competition, might have led U.S. firms to invest in "defensive" innovation independently of the incentives produced by the innovation cost-reducing policies introduced in the 1908s.[32] These are different sources of innovation and wage inequality that complement the ones studied in our paper.

9 Conclusions

In this paper we have shown both theoretically and empirically that the technological content of government procurement played a non-negligible role in explaining the wave of innovations that hit the U.S. economy in recent decades and its effects on the wage structure. The interaction between policy and the heterogeneous industry structure yields the basic theoretical contribution of the paper: a shift in the composition of public spending towards highly innovative sectors increases the aggregate expenditure in innovation and the skill premium.

The incentive to innovate produced by changes in the composition of public spending, and by R&D subsidies, are the two channels through which public policy affects technology and the wage structure. Our empirical assessment of the "policy channel" contributes to the recent literature on the endogenous determinants of skill-biased and skill-using technical change. We

[32] Thoenig and Verdier (2003) show that skill-biased innovation can be introduced by national firms in defense of their leadership threatened by increasing international competition.

identify and quantify the role of a new source of technical change, government policy, which complements the role of international trade (Dinopoulos and Segerstrom 1999 and Acemoglu 2003) and of the relative supply of skills (Acemoglu 1998 and 2002b, and Kiley 1998).

It represents a first attempt to evaluate the effects of policy on technology and wages and it is amenable to many extensions. Further research is needed to fill the data gap that prevents a more rigorous evaluation of the magnitude of the policy effects on wages. Lacking data on the technological composition of aggregate government procurement, in our empirical analyses we have used the only available sub-sample: the composition of government investment. Despite the striking validation of our theory provided by such data, a larger sample of government procurement would certainly refine the results. On the one hand, some effort should be devoted to the collection of data on the composition of public consumption between high and low-tech sectors; this would allow a better quantitative assessment of our demand-side policy channel. Moreover, it could be interesting to introduce asymmetric private spending and evaluate the relative importance of public and private spending composition in producing a demand-driven mechanism of innovation and inequality.

On the other hand, a better measurement of the magnitude of the technology transfer and intellectual property protection policies could provide a more complete assessment of the effects of the innovation cost-reducing policies introduced in the 1980s. Once in possession of better data the model could be extended with the introduction of a broader set of supply-side policy tools, such as, patent policies, as in O'Donogue and Zweimuller (2004), and a mechanism through which public technology is transferred to private firms. A calibration exercise on this extended framework could increase the fraction of inequality attributable to innovation policies.

Finally, another extension would open up our economy and endogenize the shift in technology policy making it dependent on some indicator of international competitiveness. Market-oriented technology policy could then be an optimal policy response to the loss of international competition of the U.S. economy due to trade liberalization and technology diffusion.[33]

10 Appendix

Proof of the existence of the steady state. Solving (17) for x_ω and integrating it w.r.t. ω we get:

[33] A first step in this direction is taken in Impullitti (2005).

$$\overline{x} = \frac{\theta_0 - \gamma}{b\sigma(\rho + n/\mu - n)} \left[(\theta_0 - \Omega) \left(\Gamma^{-1} - 1 \right) + (\overline{G} - \Omega) \right] \tag{A1}$$

and substituting this into (18) we obtain the following synthetic equilibrium condition:

$$(\theta_0 + 1 - 2\gamma)(1 - \theta_0)\phi/2 = \frac{n(\theta_0 - \gamma)}{\mu\sigma(\rho + n/\mu - n)} \left[(\theta_0 - \Omega) \left(\Gamma^{-1} - 1 \right) + (\overline{G} - \Omega) \right]. \tag{A.1.1}$$

The LHS of this eq. (A11) is a strictly concave quadratic polynomial with roots on $2\gamma - 1$ and 1, and the RHS of eq. (A11) is a strictly convex quadratic polynomial with roots γ and $\frac{\Omega - \Gamma\overline{G}}{1-\Gamma}$. It follows that, if the stated parameter restrictions are satisfied, there exists always one and only one real and positive solution $\theta_0 \in (\gamma, 1)$. The proof follows from the fact that the specified parameter restriction allows the intercept (the value of the polynomial at $\theta_0 = 0$) of the LHS polynomial to be bigger than in intercept of the RHS polynomial. Specifically $LHS(0) > RHS(0)$ implies:

$$(1 - 2\gamma)\phi/2 > \frac{n\gamma}{\mu\sigma(\rho + n/\mu - n)} \left(\frac{\Omega - \Gamma\overline{G}}{\Gamma} \right),$$

which rearranged leads to the parameter restriction. It is easy to see that this condition allows for a unique solution[34]. Moreover for Minkowski's inequality $\Omega - \Gamma\overline{G} < 0$, therefore when $1 - 2\gamma > 0$ no restriction on parameters is needed for a unique solution.

Proof of Proposition 1.a. Solving (17) for x_ω we get:

$$\left(\frac{\lambda_\omega - 1}{\lambda_\omega} \right) \left(\frac{\theta_0 - \Omega}{\Gamma} + G_\omega \right) \frac{\theta_0 - \gamma}{b\sigma(\rho + n/\mu - n)} = x_\omega,$$

and deriving w.r.t. $G_\omega$we obtain

$$\frac{\partial x_\omega}{\partial G_\omega} = \left(\frac{\lambda_\omega - 1}{\lambda_\omega} \right) \frac{\theta_0 - \gamma}{b\sigma(\rho + n/\mu - n)},$$

which is always positive since $\lambda_\omega > 1$, $\theta_0 > \gamma$ and $\rho > n$. From this derivative we can also see that $\partial x_\omega / \partial G_\omega > \partial x_{\omega'} / \partial G_{\omega'}$ when $(\lambda_\omega - 1)/\lambda_\omega > (\lambda_{\omega'} - 1)/\lambda_{\omega'}$ which is always true if $\lambda_\omega > \lambda_{\omega'}$.

Proof of Proposition 1.b Rearranging (A11) we get a single polynomial in θ_0 and Ω:

[34]It is easy to check that all parameters restriction are satisfied by the number we use in the calibration excercise.

$$F(\theta_0;\Omega)=\frac{n(\theta_0-\gamma)}{\mu\sigma(\rho+n/\mu-n)}\left[(\theta_0-\Omega)(\Gamma^{-1}-1)+(\overline{G}-\Omega)\right]-(\theta_0+1-2\gamma)(1-\theta_0)\phi/2. \tag{A.1.2}$$

Using the Implicit Function Theorem we get:

$$\frac{d\theta_0}{d\Omega}=\frac{-\partial F/\partial\Omega}{\partial F/\partial\theta_0}=$$

$$=\frac{\frac{n(\theta_0-\gamma)}{\mu\sigma(\rho+n/\mu-n)\Gamma}}{\frac{n}{\mu\sigma(\rho+n/\mu-n)}\left[(\theta_0-\Omega)(\Gamma^{-1}-1)+(\overline{G}-\Omega)\right]+\frac{n(\theta_0-\gamma)}{\mu\sigma(\rho+n/\mu-n)}(\Gamma^{-1}-1)+\phi(\theta_0-\gamma)}>0$$

This results follows from the fact that $\theta_0>\gamma$, $\rho>n$, $\Gamma^{-1}>1$ and finally, from (A1) we know that the expression inside the square brackets is greater than zero.

10.1 The Research & Experimentation Tax Credit and the "structural change" in the U.S. innovation policy

The Research & Experimentation Tax Credit, part of the U.S. Internal Revenue Code, was established by the Economic Recovery Tax Act of 1981. The tax credit was part of a more general strategy implemented by policy makers in the late 1970s and in the 1980s that was directly targeted to stimulate commercial innovation and enhance the competitiveness of American firms in the global economy. This represented a substantial shift in innovation policy with respect to the post-war government practice of primarily funding military technology and obtaining commercial innovation only through spillover effects. The change might have been triggered by the recovery of European and Japanese economies from the war in the 1970's, and intensified by the eclipse of the Soviet's military power as a treat to U.S. security in the mid-1980's.[35]

In the 1980s we observe the introduction of new policy tools aimed at facilitating firms access to public technology, improve intellectual property rights and, more in general, reduce the private cost of innovation. Examples are: the Bayh-Dole Act of 1980 and the Federal Technology Transfer Act of 1986 that transformed federal laboratories into sources of innovation for U.S. firms; the establishment in 1982 of the Court of Appeals for the Federal Circuit, which improved

[35] For an interpretation along these lines see Ham and Mowery (1999).

the protection granted to patents holders; the National Cooperative Research Act of 1984, which reduced antitrust persecutions of joint ventures for pre-commercial research. Mowery (1998) describes this set of policies as a "structural change in the U.S. national innovation system". There is a sufficient consensus among technology policy scholars that the post-1980 policy shift, started during the Reagan and Bush administrations and continued as a trademark of Clinton's economic policy, represents a crucial move towards an explicit commercial innovation policy in the U.S. history.[36]

Unfortunately there is no available quantitative measures of the effects of technology transfer and of property rights policies on the cost of innovation. For lack of data we focus only on the effects of the R&E tax credit on innovation and inequality. Hall (1993) estimates the average effective R&D credit rate relative to the R&E Tax Credit by computing the reduction in the tax price of R&D produced by the credit. The estimated effective rate fluctuates between 3 and 7 percent of the cost of R&D in the period 1981-91. Thus, although the legislation set the official credit rate around 20 per cent, the effective credit rate has been on average around 4 per cent of R&D at the firm level. This gap is due to the incremental design of the credit: by increasing the current R&D investment a firm will increase its current total tax credit but it will also raise the base level of R&D above which the credit is granted for the following three years.[37] Although the credit rate has been pretty constant over the years its incremental feature was designed to generate a persistent incentive for private firms to increase their R&D investment over time.

References

[1] Acemoglu D. (2002a). "Technical Change, Inequality and the Labor Market", *Journal of Economic Literature*, XL, pp. 7-72.

[2] Acemoglu D. (2002b). "Directed Technical Change", *Review of Economic Studies*.

[36] For a more detailed analysis of the changes in technology policy in the 1980s see Mowery and Rosenberg (1989), Mowery (1998), Branscomb and Florida (1998), Mirowsky and Sent (2005).

[37] We can illustrate the point with a simple example taken from Mammuneas and Nadiri (1997). If the official credit rate is 25 per cent, the cost to the firm of \$1 of incremental R&D would be reduced by \$0.25. However, the \$1 increase in R&D decreases the tax credit for the next three years by $\$0.33x0.25 = \$0.083$ for each year. With a discount rate if 10 per cent the effctive tax reduction of a \$1 increase of R&D spending is $\$0.25 - \left(\sum_{i=1}^{3} \$0.083/\left(1=0.1\right)^{i}\right) = \$0.045$. Thus, the official tax credit rate of 25 per cent becomes an effective rate of 4.5 per cent.

[3] Acemoglu, D. (2003). "Patterns of Skill Premia", *Review of Economic Studies*, volume 70, pp. 199-230.

[4] Aghion, P. (2002). "Schumpeterian Growth Theory and the Dynamics of Income Inequality," *Econometrica* 70(3): 855-882.

[5] Aghion, P., P. Howitt, and G. Violante. (2002). "General Purpose Technology and Wage Inequality," *Journal of Economic Growth*, vol. 7(4), December 2002, 315-345.

[6] Baily, M. N., and R. Z. Lawrence. (1992). "Tax Incentives for R&D: What do the Data Tell Us?," Council on Research and Technology, Washington, D.C..

[7] Berman, E., J. Bound, and Z. Griliches, (1994). "Changes in the Demand for Skilled Labor within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufactures," *Quarterly Journal of Economics*, Vol. 106, No. 2, pp. 367-397.

[8] Bloom, N.,Griffith R. and J. Van Reenen (2002). "Do R&D Tax Credits Work?". *Journal of Public Economics*, 85 1-31

[9] Branscomb L. and R. Florida (1998). "Challenges to Technology Policy in a Changing World Economy", in L. Branscomb and J. Keller (Eds.), *Investing in Innovation: Creating a research and Innovation Policy that Works*. MIT Press, Cambridge. Massachusetts.

[10] Caselli, F. (1999). "Technological Revolutions," American Economic Review, 89, 1, 78-102.

[11] Cummins J., and G. Violante (2002). "Investment-Specific Technical Change in the US (1947-2000): Measurement and Macroeconomic Consequences", *Review of Economic Dynamics*, vol. 5(2), April 2002, 243-284.

[12] Dinopoulos E. and P. Segerstrom. (1999). "A Schumpeterian Model of Protection and Relative Wages," *American Economic Review* 89, 450-472.

[13] Engle R. and B. Yoo (1987). "Forcasting and Testing in Co-Integrated Systems", *Journal of Econometrics 35, 143-159.*

[14] Finkelstein, A. (2003). "Health Policy and Technical Change: Evidence from the Vaccine Industry." NBER Working Paper #9460.

[15] Galor Oded and Omer Moav, "Ability Biased Technological Transition, Wage Inequality, and Economic Growth," *Quarterly Journal of Economics* , 115, May, 469-498.

[16] Gort M, Greenwood J., and P. Rupert (1999). "Measuring the Rate of Technological Progress in Structures," *Review of Economic Dynamics*, 2, 207-30

[17] Grossman G. M. and E. Helpman. (1991). Innovation and Growth in the Global Economy. Cambridge: MIT Press.

[18] Hall, B. (1993). "R&D Tax Policy During the Eighties: Success or Failure?" *Tax Policy and the Economy* 7: 1-35.

[19] Ham, R. M., and D. Mowery. (1999). "The U.S. Policy Response to Globalization: Looking for the Keys Under the Lamp Post", in J. Dunning, ed., *Governments and Globalization*, Oxford University Press.

[20] Hart, D. (1998). "US Technology Policy: New Tools for New Times", *NIRA Review*, Summer 1998.

[21] Hatzichronoglou, T. (1997). "Revision of the High-Technology Sector and Product Classification", *OECD STI Working papers* GD (97) 216.

[22] Hobijn, B. (2001a)."Is Equipment Price Deflation a Statistical Artifact?" *FRBNY Staff Report* #139, November.

[23] Hobijn, B. (2001b). "Embodiment in U.S. Manufacturing". FRBNY mimeo.

[24] Hornstein, Andreas, Per Krusell, and Gianluca Violante (2005). "The Effects of Technical Change on Labor Market Inequalities," *Handbook of Economic Growth*, (Philippe Aghion and Steven Durlauf, Editors), North-Holland.

[25] Impullitti, G. (2006). "International Competition, Growth, and Optimal R&D Subsidies," mimeo NYU.

[26] Jones C. (1995). "Time Series Tests of Endogenous Growth Models", *Quarterly Journal of Economics* 110, 495-525.

[27] Jones C. (2005)."Growth in a World of Ideas", *Handbook of Economic Growth*, forthcoming.

[28] Jones C. and J. Williams (2000). "Too Much of a Good Thing? The Economics of Investment in R&D", *Journal of Economic Growth*, Vol. 5, No. 1, pp. 65-85.

[29] Kiley, M. (1999). "The Supply of the Skilled Labor and Skill-Biased Technological Progress", *Economic Journal*. 109, pp.708-724.

[30] Krusell, P., L. Ohanian, J.V. Rios-Rull and G. Violante (2000): "Capital-Skill Complementarity and Inequality", *Econometrica*, 68:5, 1029-1054.

[31] Lictenberg, F.R. (1995). "Economics of Defense R&D," in Hartley, Keith and Sandler, Todd ed. *Handbook of Defense Economics*, New York, Elsevier Science B.V.

[32] Machin, S. and J. Van Reenen (1998). "Technology and Changes in Skill Structure: Evidence From Seven OECD Countries", *Quarterly Journal of Economics* 113, 1215-44.

[33] Mammuneas, T. and I. Nadiri (1996). "Public R&D Policy and Cost Behavior of the U.S. Manufacturing Industries," *Journal of Public Economics*, 63, 57-81.

[34] Mehra,R., and E.C.Prescott.(1985). "The Equity Premium: A Puzzle," *Journal of Monetary Economics* 15, 145-161.

[35] Mirowsky, P. and E.-M. Sent, (2005). "The Commercialization of Science, and the Response of STS", in *New Handbook of Science and Technology Studies*, MIT Press, forthcoming.

[36] Mowery, D. (1998). "The Changing Structure of the U.S. National Innovation System: Implications for International Conflict and Cooperation in R&D Policy," *Research Policy* 27, 639-654.

[37] Mowery, D. and N. Rosenberg (1989). *Technology and the Pursuit of Economic Growth*, Cambridge University Press.

[38] National Science Foundation (2002). *Science and Engineering Indicators 2002.*

[39] O'Donoghue, T. and J. Zweimuller (2004). "Patents in a Model of Endogenous Growth," *Journal of Economic Growth*, 9(1),81-123.

[40] O'Hanlon, M. (2000). *Technological Change and the future of Warfare*. Brookings Institution Press, Washington, D.C.

[41] Roeger, W. (1995). "Can Imperfect Competition Explain the Difference between Primal and Dual Productivity Measures? Estimates for US Manufacturing", *Journal of Political Economy* 103, 2, 316-330.

[42] Ruttan, V. P. (2003). "Military Procurement and Technology Development", University of Minnesota, mimeo.

[43] Segerstrom P. (1998). "Endogenous Growth Without Scale Effects", *American Economic Review* 88, 1290-1310.

[44] Thoenig, M. and T. Verdier, (2003). "A Theory of Defensive Skill-Biased Innovation and Globalization," *American Economic Review*, 2003, vol. 93, 3, pp. 709-728.

[45] Van Reenen, J. (1997). "Why Has Britain had slower R&D growth?" *Research Policy* 26, 493-507.

[46] Violante, G. (2002). "Technological Acceleration, Skill Transferability and the Rise of Residual Inequality," *Quarterly Journal of Economics*, vol. 117(1), February 2002, 297-338.