Technology Policy and Wage Inequality

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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.

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1 Introduction

In the early 1980s we observe a substantial increase of public investment in high-tech sectors in the U.S.: 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.[1] 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 (NSF 2002). Accompanying this acceleration of the technological intensity of public spending we observe an 18 percent increase in the relative wage of skilled workers during the 1980s (CPS 1999).

In this paper we argue that the 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. As innovation is a skill-using activity, government policy may have also helped to stimulate the relative demand for skills and raise the skill-premium. Our analysis remarks that although government procurement is not an explicit policy tool, it has often worked as 'de facto' innovation policy instrument.

We build a version of the quality-ladder growth model with endogenous supply of skills (Dinopoulos and Segerstrom 1999). A new and key feature of our model is the introduction of heterogeneous industries. The economy is populated by a continuum of monopolistic competitive industries 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, where each sector gets the same share of public spending, to an asymmetric rule, meaning that the sector with the highest quality jump receives the greatest amount of government 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 assume that unskilled labor is used exclusively in manufacturing and that ideas are produced using only skilled labor. As the government reallocates spending from low

[1] E&S includes a group of investment goods that are considered more innovative than those included in structures (see Cummins and Violante 2002 and Hobjin 2001b).

to high-tech sectors, aggregate profits increase. Intuitively, higher quality jumps in high-tech sectors imply higher mark-ups and larger profits. Hence, a redistribution of public spending in favor of these sectors raises aggregate profits in the economy. In quality-ladder growth models monopoly profits are the rewards for innovation activities, so the increase in total profits produced by the reshuffling of public spending will raise the relative demand for skilled workers.

Finally, there is a training choice in the model that endogenizes skills formation. This implies that, by increasing the skill premium, high-tech public spending will also raise the incentives to train and accumulate skills. Therefore, wage inequality generated by our source of technical change will be a general equilibrium result, where both the supply and the demand for skills are endogenous.

We adopt a broad interpretation of innovation in order to include all of those activities that are targeted to increase firm 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 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).[2] Like other works in this area, 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).[3] 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 an 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

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

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

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 Dinopoulos and Segerstrom (1999) version of the quality-ladder growth model. With respect to that work our contribution is the following: first, on the theory side, the presence of asymmetric industries allows government spending to affect innovation and the skill premium. This is not obtainable by simply introducing government spending into Dinopoulos and Segerstrom's symmetric framework. Second, while their application focuses on trade liberalization as the source of technical change and wage inequality, we examine the role of government policy. To our knowledge, this is the first attempt to assess the relevance of the public '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 intuition for the macroeconomic consequences of asymmetric steady states. In section 6 we calibrate the model to match salient long-run facts of the U.S. economy and perform a quantitative evaluation of our theoretical mechanism. Section 7 provides remarks on the qualitative and quantitative predictions of the model. Section 8 concludes.

2 Stylized facts

In this section we provide some background evidence on the dynamics of public spending composition and wage inequality in recent decades. 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). Hence, according to this view, 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 (see Ruttan 2003, and Finkelstein 2003).

In this paper we propose an aggregate measure of this demand-pull channel for innovation. We use BEA NIPA data that breaks-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. The focus on investment is due to the fact that there is no aggregate data keeping track of the technological composition of public consumption expenditures.

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 from a fairly steady course to a rapidly increasing one during the late 1970s early 1980s. This common and contemporaneous trend change suggests that the shift towards high-tech public spending, which began around 1974 and radically accelerated around 1978, might have had an influence on rising inequality in the 1980s.[4]

[FIGURE 1 ABOUT HERE]

Using the same data we find that also the composition of private investment progressively shifted towards E&S since the late 1970s. However, the technological composition of public investment accelerated in the 1980s -the period when wage inequality increased more rapidly- while the rise of private investment in E&S was concentrated in the 1990s. More precisely, the yearly average growth rate of private investment was 9 percent while the growth rate of public investment was 16 percent in the period 1970-90; while private spending jumped on those high growth rates only in the 1990s.[5]

As R&D represents an important part of innovation activity, figure 2 shows that, as was the case for the composition of public spending, the trend of private R&D/GDP also increases substantially in the late 1970s, along with that of the skill premium.[6]

[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.

[5] We also find that the ratio of public to private investment in the innovative aggregate has been betwen 13 and 26 percent in the period 1970-90. This indicates that the scale of public E&S is not negligible in the period of interest.

[6] The technological composition of government procurement affects the market-size of all kinds of innovation activities, of which R&D is a relevant component.

[FIGURE 2 ABOUT HERE]

Next, we explore more in detail the properties of the data. We perform a preliminary econometric analysis to test the correlation between the variables of interest. We would like to emphasize that our goal here is not to establish causality but only to show some key correlations that motivate our analysis. The calibration exercise in section 6 will provide a structural evaluation of the quantitative effect of public spending on wage inequality.

We consider only one dimension of innovation activities, R&D investment, and look for a positive correlation between government spending, innovation and the skill premium. First, we regress private investment in R&D, as a share of GDP, to the composition of public spending for the period 1953-2001.

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.

We find that private R&D is positively correlated with public investment in E&S as a share of total public investment.[7]

We also look at what the data say about the relationship between non-federal R&D expenditure and the skill premium. Here we have shorter time series, 1963-1999, due to skill premium data availability, but the results are good, as shown in the following table II below.[8] We find

[7]The constant is not displayed in table I because it was not significant even at 10%. Some comments on some of the standard diagnostic tests we performed are necessary. First, the Ljung-Box Q test rejects the null hypothesis of residuals autocorrelation. We also performed the Breusch-Godfrey Lagrange multiplier tests and we were able to reject the null hypothesis of serial autocorrelation at all lags - the one showed in table I is for four lags. Second, both explanatory variables, when subjected to an Augmented Dickey-Fuller (ADF) test do not prove stationary. Therefore, we performed the ADF test on the regression residuals: the test statistics is equal to -5.6633, which also passes the stricter Engle and Yoo (1987) version of the unit root test. Hence, the regression results can be considered fairly reliable.

[8]Here again we deal with two non-stationary series, so the basic reliability of the regression is obtained running the same battery of tests that we discussed in the previous footnote. The Q and the LM-tests rejects serial autocorrelation of residuals, and statistics of the ADF test on residuals in this case is -5.5058. This allows us to consider the regression results sufficiently accurate.

and positive and significative correlation between investment in R&D and the skill premium.

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.

The results in table II are qualitatively in line with those of more extensive and specific empirical studies. For instance 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. 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.

We can now wonder how the two correlations showed above concur in a unique indirect correlation between public investment composition and the skill premium. This is assessed by directly regressing the skill premium to the composition of public spending, as reported in the next regression table III.[9] Again we find a positive and significative correlation.

[9] As with the previous two regressions the Q and LM-tests allowed us to reject serial correlation of residuals at all lags. The ADF statistics was -5.8179, which again passes also the stricter Engle and Yoo test.

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.

In our opinion this set of facts and preliminary evidence provide a sufficient motivation to dig deeper into the links between public spending composition, technology, and wage inequality.

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 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

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

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

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

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 where $r(t)$ 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 good ω is available at time t. As is common in quality ladders models, we assume price competition[10] 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, implying 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 exogenous duration of their life[11]. 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, is set 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

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

[11] 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 $t + D$.

to accumulate skills (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 where w_L, w_H, and c_θ are all constant. It 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 that the unskilled wage becomes 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:

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

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 returns 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.

As usual in Schumpeterian models with vertical innovation (see e.g. Grossman and Helpman, 1991, and Aghion and Howitt, 1992) the next best-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 patentholder 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 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[12] 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 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:

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

Our fiscal policy tool will be sector specific per-capita public 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 are 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 expenditures.

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. Sectorial market-clearing conditions imply that demand equals production of every consumption good by the firm that monopolizes it, q_ω. It follows that the stream of 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

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

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

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

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

3.3 Innovation races

In each industry leaders are challenged by the innovation activity of 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 her 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 that generate 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.[13] In the present framework with quality-improving consumer's goods "growth" is interpreted as the increase of the representative consumer utility level over time.

[13] 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.

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

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

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 wage.

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

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

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, the skilled labor market equilibrium implies:

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

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 increase in government spending in sector ω stimulates innovation in that specific industry 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 become clearer later; for the moment it suffices to note that it shows that the share of unskilled workers θ_0 is increasing with the technology-adjusted average government spending Ω.[14]

5 Fiscal policy rules

Here we specify rules for public spending and derive the basic result 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 $G_\omega = \overline{G}\frac{\lambda_\omega}{\overline{\lambda}}$. A 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 $0 \leq \alpha \leq 1$.

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

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

Proof. The general rule yields $\Omega = \overline{G}\left[\int_0^1 \frac{1-\alpha}{\lambda_\omega} d\omega + \frac{\alpha}{\lambda}\right]$ and deriving Ω with respect to α we obtain $\partial\Omega/\partial\alpha = \overline{G}\left[-\int_0^1 \frac{1}{\lambda_\omega} d\omega + \frac{1}{\lambda}\right]$: Jensen's inequality implies that $\partial\Omega/\partial\alpha < 0$. Thus, a shift to more asymmetric spending (an increase in α) decreases Ω that, according to Proposition 1.a, generates a decrease in the share of the population that decides not to acquire skills, θ_0. Recalling that the skill premium is $w_H = \sigma/(\theta_0 - \gamma)$, we conclude that a 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 there is an increase in the relative supply of skilled workers and an increase in the skill premium.[15] This result is directly related to our asymmetric-industry setting. One dollar of public money in high-tech sectors yields more additional profits than those lost taking one dollar away from low-tech sectors, and the net result is an increase in aggregate profits and innovation activity.[16] When industries are symmetric the profit rate is the same in all industries and aggregate profits are not affected by a reshuffling of government spending.

It is worth stressing that the effect of public spending composition on innovation and growth takes place only along the transition to the steady state. We work with a semi-endogenous framework where long-run growth is pinned down by the growth rate of population ($I = n/\mu$). Although steady state growth rates are not affected, policies altering the scale innovation will have a permanent impact on the levels. Hence, the steady state relative labor demand and supply will change according to our findings in proposition 2.

6 Quantitative analysis

Regression results in section 2 suggest that the model identifies an important link. In this section we try to measure the quantitative relevance of our mechanism by calibrating a two-sector version of the model.[17] Since the only available data on public spending composition concern investment, in the calibration exercise we need to reinterpret the model in terms of intermediate goods. As is common in the literature an alternative interpretation of quality-ladder models is one where households consume a homogeneous consumption good which is

[15] This theoretical result matches two well known stylized facts of the U.S. labor market (see Acemoglu 2002a figure 1).

[16] From (9) we know that λ_ω coincides with the markup over the unit cost for the sector ω. It follows that markups are higher in high-tech sectors.

[17] All the results obtained for the model with a continuum of sectors hold for this simplified version.

assembled from differentiated intermediate goods. The static utility function in (1) can be then interpreted as a CRS production function where superior quality intermediate goods are more productive in manufacturing the final good.[18]

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 their average life time. 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 two 5-years periods, 1976-80 and 1987-91.[20] We 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 compare it with the actual increase observed in the data.

The calibration of some parameters is standard. We set ρ, which in the steady state is equal to the interest rate r, to 0.07 to match the average real return on the stock market of 7 percent for the past century, estimated in Mehra and Prescott (1985).[21] We calibrate n to match a 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 must be 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 U.S. manufacturing firms. We use the

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

[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 reasonably 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. We limit the analysis to the period 1976-91 because these are the years where the bulk of the increase in the U.S. skill premium took place (see figure 1).

[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.

revised OECD classification of high-tech and low-tech sectors as in Hatzichronoglu (1997)[23]. Roeger (1995) estimates sectorial markups for the period 1953-84, we take the lower bound of both high-tech and low-tech groups in these estimates, that is, we consider a 15 percent and a 34 percent markup for low and high-tech respectively[24]. In our 5-year time frame this implies setting $\lambda_1 = (1 + 0.15 * 5) = 1.75$ and $\lambda_2 = 1 + 0.34 * 5 = 2.7$.

Once we have 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 the Penn World tables we take 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 0.47, 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 in (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, reducing the system to one equation - as

[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. 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.

[24] We take the lower bounds of Roeger's estimates because we want to provide a baseline calibration with reasonable markup levels. Too high markup levels would inflate incentives to innovate in the model and lead to an overstatement of the results. We also performed the calibration with the average markups in Roegers (1995) weighted with the sectoral output share. This leads to an average markup of 45 percent and in low-tech and of 70 percent in high-tech sectors. In the comparative static exercise we obtain results similar to those reported below.

[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. Using sectoral output shares, for instance, we obtain a 51 percent high-tech share and a 49 percent low-tech share.

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

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 $\frac{G_2}{c}$):

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

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 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	lower-bound for the share of unskilled	Dinopoulos-Segerstrom 1999
μ	0.47	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)

To asses the effect of public spending on wages 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 periods of interest: in 1976-80 average government investment in structure was 29 percent and in E&S was 7 percent of total private investment ($\frac{G_1}{c} = 0.29$ and $\frac{G_2}{c} = 0.07$); respectively, in 1987-91 the low-tech expenditure share decreased to 26 percent and the high-tech share rose to 18 percent. In our calibrated model this change in the composition of public spending in favor of high-tech sectors produces 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

[27]Notice that here we do not exactly use the fiscal policy rules specified in section 5. This is because when in this simplified 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 data 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 data in the quantitative excercise we use directly government investment in the two sectors, as a share of total private investment, as an index of spending composition.

percent. Hence, our demand composition shock can explain 12 percent of the total increase in the skill premium shown in the data.[28]

We also explore the sensitivity of the results to changes in the difference in 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 weighted markup of 79 percent - the weights are sectorial output shares. These changes increase the percentage of the observed skill premium explained by the model from 12 to 24 percent. Hence, the quantitative importance of our mechanism increases with the technology gap between low and high-tech sectors.[29]

7 Discussion

In this section we provide a discussion on the predictions of the model and on the quantitative results obtained.

Within and between-industry changes. In our model the demand-composition shock produces skill-upgrading in high-tech sectors and de-skilling in low-tech sectors. Recent empirical works have showed that skill-upgrading and increasing wage inequality took place in both high-tech and low-tech sectors in the period of interest, with higher intensity in the former group of industries (see i.e. Machin and Van Reenen,1998). Our results cannot fully match this empirical evidence. Here two remarks are needed: first, we do not claim that our source of innovation is the only one that might have played a role in explaining the observed dynamics of technical change and wage inequality. Second, even restricting the focus on the 'policy channel' our analysis is limited to a single, demand-side, policy tool. It is likely that supply-side innovation policies, such as R&D subsidies and technology transfer, might also have affected technology and wages in recent years. For instance, the introduction in 1981 of R&D subsidies through the Research and Experimentation (R&E) Tax Credit, by reducing the after-tax cost

[28] The measure of inequality that we use, w_H/w_L, might overstate the increase in the skill premium when we bring the model to the data. This happens because 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. Hence, 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.

[29] It is worth to notice that the substantial but relatively small amount of inequality explained by our mechanim might be biased downward by the lack of data on the technological composition of public consumption.

of innovation might have increased the relative demand for skills and the skill premium in all sectors of the economy. Introducing R&D subsidies in the model would allow us to have a policy tool that produces skill-upgrading in all industries symmetrically. The extent to which R&D subsidies would compensate for the negative skill-upgrading in low-tech industries produced by government expenditures will depend on the parameters of the model and on the relative strength of the two types of policies.

In appendix B we have extended the model to include a simple symmetric subsidy to R&D.[30] We have used Hall (1993) estimates of the effective credit rate produced by the R&E Tax Credit, and measured the effects of R&D subsidies on wage inequality. The annual across-sectors average credit rate varies between 3.04 percent in 1981 and 7.49 percent in 1991.[31] In our starting period, 1976-80 the credit is 0, and in the ending period, 1987-91, the average credit rate is estimated to be around 4 percent per year. In our calibrated model this subsidy shock produces a 3.2 percent increase in the skill premium, accounting for about 18 percent of the real change in the skill premium over the period. Hence, when we introduce a supply-side policy tool, 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 with the evidence in Machin and Van Reenen (1998).

Moreover, 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. They also find that the primary source of inequality induced by between-industry changes was explained by defense procurement.[32] Our findings are not far from this general picture.

Finally, 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.[33] Cummins

[30] Appendix B is available upon request.

[31] The credit rate was initially set at 25 percent of "incremental" R&D: 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 fairly constant, its incremental feature generates a persistent incentive for private firms to increase their R&D investment over time.

[32] 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).

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

and Violante (2002) find the average technical change in E&S over 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 shown that, although technical change in structures is less relevant than 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 during 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.

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 on the wage structure. According to the facts discussed in section 2 we expect that the shift in public spending composition will be relatively more important in the 1980s, and private spending composition will be the main factor in the 1990s.

8 Conclusions

In this paper we have shown that the technological content of government procurement played a significant 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 aggregate expenditure in innovation and the skill premium.

We 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 is worth stressing once again that our model is not, strictly speaking, a model of skill-biased technical change. However, introducing endogenous factor-bias in the set-up and assuming that high-tech goods are produced by skilled workers and low-tech goods by unskilled workers, the composition of government spending would have the same qualitative effects on inequality.

This paper represents a first attempt to evaluate the effects of policy on technology and wages and 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 support for our theory provided by such data, a larger sample of government procurement would certainly refine the results. Hence, some effort should be devoted to the collection of data on the composition of public consumption between high-tech and low-tech sectors; this would allow for a better quantitative assessment of our demand-side policy channel. Moreover, it would 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.

A second line of future research would involve a more complete investigation of the 'policy channel' by explicitly introducing into the model some supply-side policy tools that might have contributed to increase private incentives to innovate in the 1980s. In this period, in fact, we observe the introduction of new policy tools aimed at facilitating firms' access to public technology, improve intellectual property rights and, more in generally, reduce the private cost of innovation. The introduction of the Research and Experimentation Tax Credit in 1981 discussed in the previous section; the Bayh-Dole Act of 1980 and the Federal Technology Transfer Act of 1986, which 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 the protection granted to patents holders; the National Cooperative Research Act of 1984, which reduced antitrust prosecution 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 sufficient consensus among technology policy scholars that the post-1980 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..[34]

Finally, our basic theoretical finding highlights a mechanism of 'zero-cost' growth policy that

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

can be relevant for recent policy debates, especially in those countries that, burdened by large public debt, wish to stimulate growth without using deficit spending. For instance, low-cost growth policies have recently played a central role in the implementation of the Lisbon Agenda in the E.U.. (see Sapir 2003).[35] In our semi-endogeous set-up reshuffling public expenditure in favor of high-tech sectors promotes higher economic growth along the transition to the steady state. Introducing the asymmetric industry structure into a fully-endogenous R&D-driven growth model (i.e. Dinopoulos and Thompson, 1998, Howitt, 1999, Peretto, 1998) the increase in the technological composition of government spending would increase long-run growth. This could be another interesting area of future research.

9 Appendix

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

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

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:

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

[35] For a recent survey on growth policies see Aghion and Howitt (2005).

which rearranged leads to the parameter restriction. It is easy to see that this condition allows for a unique solution[36]. 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:

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

Using the Implicit Function Theorem we get:

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

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

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.

References

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

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

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

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

[4] Aghion, P. and P. Howitt. (2005). "Appropriate Growth Policy: a Unifying Framework," Schumpeter Lecture, European Economic Association Annual Meeting, Amsterdam.

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

[6] 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.

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

[9] 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.

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

[11] Dinopoulos E. and P. Thompson. (1998). "Scale Effects in Schumpeterian Models of Economic Growth", *Journal of Evolutionary Economics*, 157-85.

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

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

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

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

[16] 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.

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

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

[19] 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.

[20] Howitt, P. (1999). "Steady Endogenous Growth with Population and R&D Inputs Growing." *Journal of Political Economy* 107, August: 715-30.

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

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

[23] 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.

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

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

[26] 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.

[27] 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.

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

[29] 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.

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

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

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

[33] Peretto, P. (1998). "Technological change and population growth", *Journal of Economic Growth*, Vol. 3, No. 4, pp. 283-311.

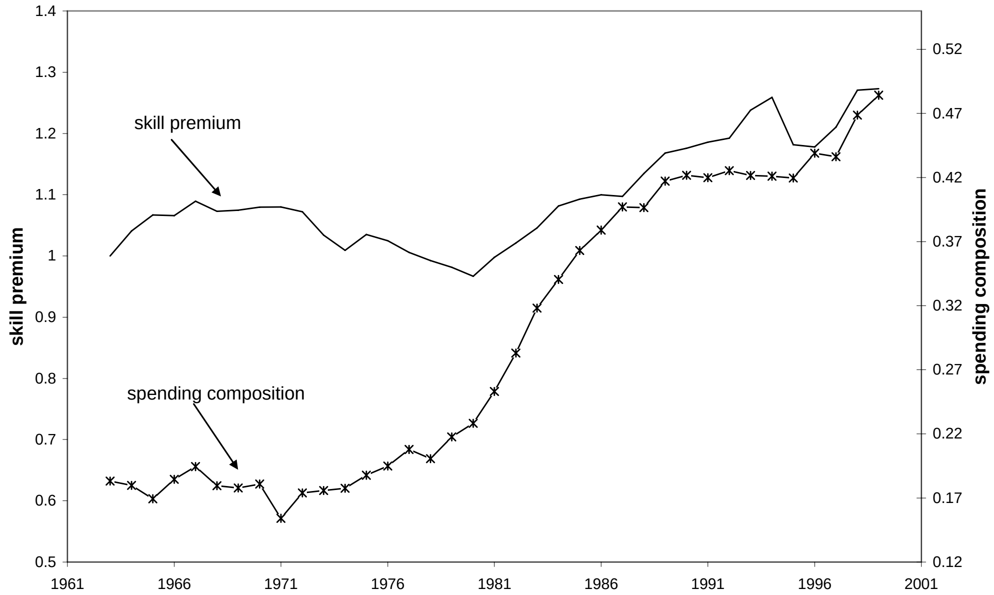
[34] Roeger, W. (1995). "Can Imperfect Competition Explain the Difference between Primal and Dual Productivity Measures? Estimates for US Manufacturing", *Journal of Political Economy* 103, 2, 316-330.

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

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

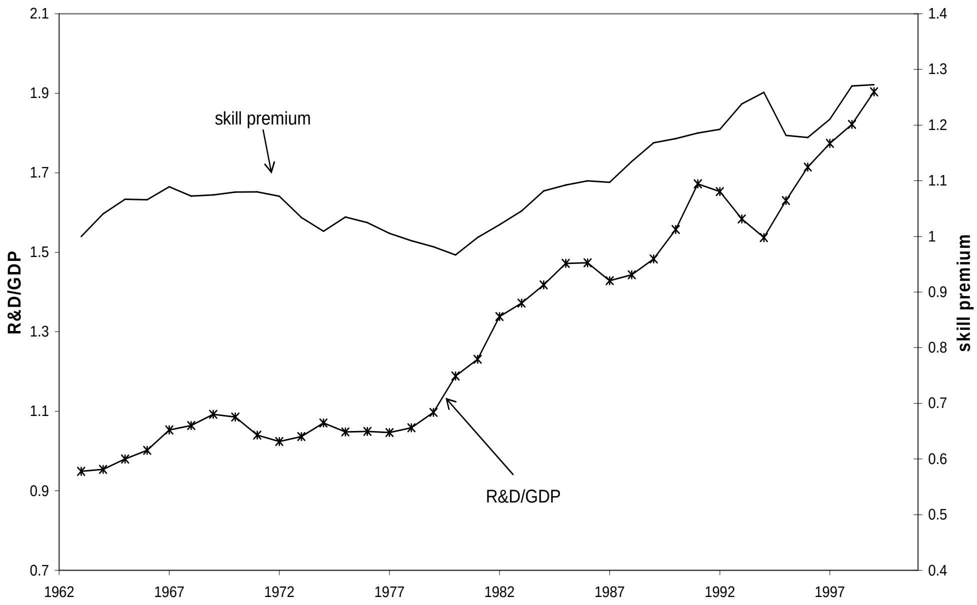
[37] Violante, G. (2002). "Technological Acceleration, Skill Transferability and the Rise of Residual Inequality," *Quarterly Journal of Economics*, vol. 117(1), February 2002, 297-338.

Figure 1. Public spending composition and the skill premium: 1963-99



Note: public spending composition is government investment in E&S as a share of total government investment. Sources: BEA, NIPA Tables section 5 for investment and Krusell, Ohanian, Rios-Rull and Violante (2000) and Current Population Survey (1999) for the skill premium.

Figure 2. Private R&D spending and the skill premium



Source: NSF, Science and Engineers Indicators 2004 and Krusell, Ohanian, Rios-Rull and Violante (2000) and Current Population Survey (1999).