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Capital vintage and climate change policies: the case of US pulp and paper

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Abstract

The climate change policy debate and ensuing discussions about industrial energy use and carbon emissions have highlighted the need to: (a) aggregate engineering information to a level relevant for economic policy analysis while maintaining sufficient detail so that results are meaningful for industry decision makers, (b) properly represent an industry's capital vintage structure to better understand inertia associated with changes in aggregate industrial emissions profiles, and (c) identify policy instruments that leverage an industry's potential for technological change such that carbon emissions can be noticeably reduced. This paper presents an econometric analysis of energy use and emissions profiles of the US Pulp and Paper Industry and uses the resulting set of equations to specify a dynamic model for the analysis of select climate change policies. Scenarios of cost of carbon, energy tax, and investment-led policies indicate that a combination of cost of carbon and investment-led policies can achieve the desired result of rapidly improving overall efficiency of the industry and promoting changes in fuel mix, which together can result in drastic reductions of carbon emissions.

Keywords: Pulp and paper industry; Climate change policy; Industrial energy efficiency; Technology policy; Engineering–economic analysis; Capital vintage; Dynamic modeling

1. Introduction

The climate change policy debate and ensuing discussions about industrial energy use and carbon emissions have highlighted the need to address in economic models several issues that have previously been relegated to the sidelines. First, there remain many non-reconciled differences in methodologies and findings from top–down and bottom–up approaches (OECD, 1998; Jacobsen, 1998). Top–down approaches are strong in capturing interrelationships between different sectors of the economy, typically assuming autonomous rates of technological change. Impacts of climate change policies are measured in terms of changes in GDP and often indicate potentially significant economic losses ranging between 1 and 2% of the GDP, given the assumed rates of technological change (Weyant, 1999). In contrast, bottom–up approaches provide detailed representations of technology features and associated abilities for technology change (OECD, 1998) but frequently suffer from an inability to link industry-specific changes to overall economic activity. The bottom–up models assume that the economy is operating within the production possibilities frontier and thus feasible cost-efficient options exist to reduce energy use and carbon emissions. Consequently, results are typically fairly optimistic about the cost of efficiency improvements and carbon emissions reductions (Sutherland, 2000), which results in the expectation that we can reduce carbon emissions possibly at a profit. Incompatibilities between bottom–up and top–down studies have led to a call by more than 100 leading international industry experts for less aggregated analytical economic modeling that can support environmental policy and investment decisions, and increased presence of engineering–economic perspectives in data collection and modeling efforts (Dowd and Newman, 1999).

Second, a growing number of industry-specific economic analyses place emphasis on the role that the age structure (vintage structure) of the capital stock or capital vintage plays for firms' input choice, rate of technology change, and environmental performance. Theoretical work dating back to Leontief (1947), Fisher (1965) and Diewert (1980) explores conditions under which an aggregate capital stock can be defined and the relevance that relative efficiencies of capital of different vintage classes have for that definition (Doms,

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1996). In this context, empirical work on specific industries, such as the pulp and paper industry explores the ability of the industry to adjust operations in light of environmental regulations (Ruth et al., 2004; Gray and Shadbegian, 1998). Such adjustment is directly linked to capital vintage as shown by Gray and Shadbegian (1998) who demonstrate that it is uneconomical and difficult for paper mills which are old and capital intensive to change their production processes in order to achieve higher efficiency or to meet environmental regulations.

Capital vintage effects have also been associated with technology and institutional lock-in (Arthur, 1994; Unruh, 2000). The incremental development of a firm's knowledge base over time produces standard operating procedures that are seen as a barrier to the adoption of new technologies. In addition, since capital investments are generally financed from a firm's own cash flow, internal investments generally are geared towards strengthening existing production processes and products. Thus, as the firm grows older it becomes less inclined to update its technologies and as a result closely follows a specific technology trajectory. Thus, initial technology choices may gradually rigidify and lock in potentially inefficient processes.

The role of industrial capital vintage structure in influencing future investment choice and effectiveness of climate change policies has led to calls for more detailed representations of capital vintage structures in general equilibrium and integrated assessment models alike (Jacobi and Wing, 1999; Sands et al., 1999).

Third, the focus on individual industries has led to calls for maximum leverage of industry-specific potentials for efficiency improvement and emissions reductions (Koomey et al., 1998; Ruth et al., 2000a, b). Identification of those potentials must be tied to economic analyses that simultaneously represent industry-specific technology with sufficient detail to identify leverage points and at an aggregate enough level to connect to economy-wide representations of the industrial system. Choosing the "right" level of aggregation can also significantly facilitate dialog about industrial change between economists and policy makers on the one hand, and decision makers in industry on the other hand.

It is in this context that the present study assesses changes in energy use and carbon emissions profiles of the US Pulp and Paper Industry. The study distinguishes between changes in demand for and production of paper and paperboard, changes in the capital vintage structure of the industry and accompanying changes in demand for seven different fuels. Econometric time series analyses are used to specify these changes through time and a dynamic engineering-economic model is developed for sensitivity analysis of the resulting system of equations and for analysis of likely impacts of alternative climate change policies on energy use and carbon emissions profiles.

The following section presents a brief overview of the US Pulp and Paper Industry and the system boundaries underlying this study. Section 3 addresses data sources and the econometric component of this study. Section 4 presents the structure and results of scenario analyses. The paper closes with a discussion of the results and their implications.

2. Industry overview

Based on energy use per dollar value of shipments, the US Pulp and Paper Industry (Standard Industry Classification (SIC) 26) ranks as the second most energy-intensive industry group in the manufacturing sector (EIA, 1997), following petroleum and coal products (Standard Industry Classification (SIC) 29). Energy intensity of pulp and paper production in the US is greater than that of pulp and paper producers in many other countries (Farla et al., 1997). In 1994, the US Pulp and Paper Industry accounted for 2.96% of total US energy consumption or 2.6 billion BTUs[1], contributing approximately 9% to total manufacturing carbon dioxide emissions (Martin et al., 2000).

For at least the last 20 years, changes in aggregate average energy efficiency in US pulp and paper production have been incremental. Key drivers behind efficiency improvements are advancements in housekeeping practices, such as better insulation, and a shift to recycled fibers, which have substantially lower total energy cost than virgin fibers (Ruth and Harrington, 1997). Efficiency improvements have also occurred through investment in new more efficient capital, but due to low turnover rates of the capital stock such investments only gradually improve efficiency. The industry also has reduced its carbon intensity by improving its energy efficiency and by switching away from carbon intensive fuels, such as residual fuel oil, and towards natural gas. Since self-generated fuels are considered carbon neutral, a switch to self-generated energy has reduced the carbon intensity of the industry as well. Currently over 56% of the industry's energy use is self-generated.

A continued increase in energy efficiency requires installation of new, more efficient capital and the simultaneous retirement of older, less efficient capital. However, the industry is the most capital-intensive manufacturing industry in the United States (Slinn, 1992). Extremely high capital costs and the high cost associated with temporary shut-downs for capital upgrades have greatly hampered the rate of capital turnover. The slow rate of capital turnover manifests itself in the slow incremental rate of technological change in the industry and is a leading reason for the gradual efficiency improvement of the aggregate capital stock. Time series analysis of capital turnover, fuel choice and efficiencies can shed light on the extent to which market dynamics for the industry's products and changes in fuel prices affect the industry's energy use and carbon emissions profiles. Exploring trajectories of the resulting set of systems equations under different technology and policy assumptions can illustrate the effectiveness of different policy interventions.

[1] 1 BTU = 0.01055 MJ.

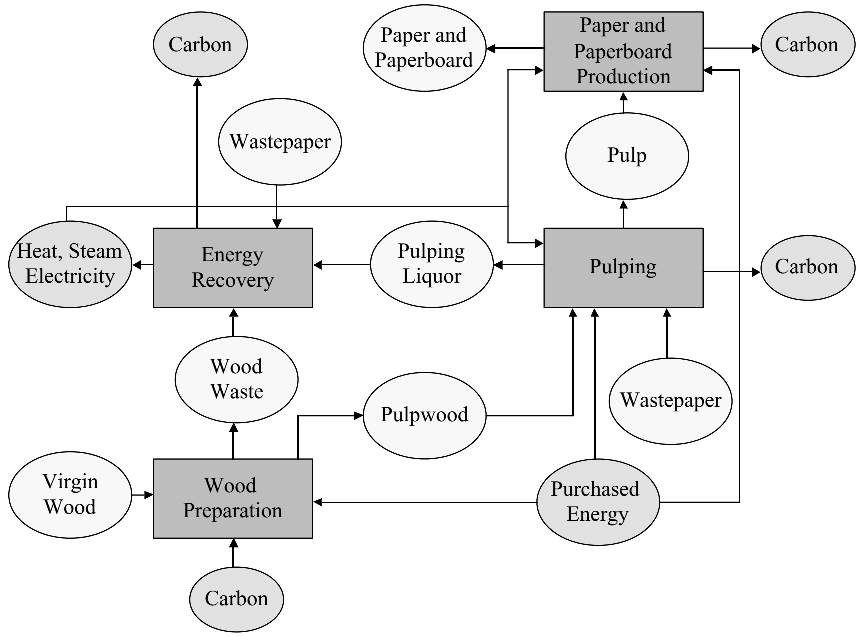

Fig. 1. System boundaries and industry components.

For the purposes of this study, we calculate demand for and supply of output from the industry, and we trace energy inputs as they enter the industry from the rest of the economy both self-generated and purchased (Fig. 1). Thus, the model contains sufficient process-specific detail to be a meaningful representation of policy and investment decision making, as has already been demonstrated in the use of earlier versions of the model in dialog between industry and policy leaders (cf. Ruth et al., 2000c). Our study, further contributes to research on the dynamics of industrial energy use and emissions by providing an application of capital vintage analysis, which has received little attention in industry specific climate change policy analysis and in industrial ecology in general.

3. Empirical analysis

3.1. Capital vintage and production capacity

To model changes in the age distribution and size of the capital stock, we apply a modified version of the perpetual inventory methods pioneered by Jorgenson (1968, 1996). The end-of period capital stock at time t is typically estimated as a function of gross new capital investments (I_t), existing capital stock (K_{t-1}) in the previous year ($t-1$) and rate of replacement (μ), where all variables are measured in monetary units:

$$K_t = I_t + (1 - \mu) \times K_{t-1} \quad (1)$$

Table 1
Regression results for investment and capacity (t-statistics in parenthesis)

Dependant variables					
Regressors	Functional form and lags	Demand (1000 short tons)	New investment (log n \$1000)	New capacity (1000 short tons)	Production (1000 short tons)
Constant		566608.14 (15.54)	12.18 (26.13)	1210.69 (6.25)	−3498.36 (−17.57)
GDP/population (\$1994)		3.37 (6.64)			
Indexed product price (1982=100)	$t-1$	−379.47 (−3.38)			
Demand (1000 short tons)	$t-1$				0.971 (14.63)
New investment (\$1000)	$t-1$			0.00038 (5.63)	
Production (1000 short tons)	$t-2$		0.00003 (5.58)		
Adjusted R[a]2		0.92	0.92	0.60	0.95
LM χ^{2}[b]		1.487 (0.779)	2.370 (0.503)	3.484 (0.332)	2.375 (0.498)
LM $\chi^2(1)$[b]		0.664 (0.553)	1.522 (0.099)	1.302 (0.132)	0.803 (0.777)

[a] Lagrange multiplier estimate of serial correlation (Breusch and Pagan, 1979), significance level in parenthesis.
[b] Lagrange multiplier estimate of heteroscedasticity (Godfrey, 1978), significance level in parenthesis.

Table 2
Regression results for industrial energy use module (t-statistics in parentheses)

Dependent variables								
Regressors	Functional form and lags	Energy efficiency ($\log n$), Million BTU/tons)	Natural gas (billion BTU)	Coal (log) (billion BTU)	Residual fuel oil (billion BTU)	Electricity (billion BTU)	Self-generated energy ($\log n$) (billion BTU)	Distillate fuel oil (% of total energy use)
Constant		4.115 (42.386)	−4554312.680 (−4.644)	13.690 (72.179)	3177127.123 (7.202)	−1655197.175 (−33.767)	6.061 (8.614)	0.046 (2.734)
Cumulative production index	$\log n$	−0.161 (−5.841)						
Cumulative paper production	$\log n$				−201155.338 (−6.29069)			
Total paper production (1000 tons)	$\log n$		452685.329 (4.996)	−0.00000405 (−2.238)		167456.253 (34.975)	0.703 (10.886)	−0.003 (−2.297)
Coal price/electricity price	(t−2)			−4.262 (−12.019)				
	(t−4)			−0.943 (−3.218)				
Residual fuel oil price ($ per million BTU)	$\log n$ (t−2)				−134765.520 (−7.7281)			
Average energy price[a] ($ per million BTU)	(t−3)						0.028 (5.664)	
Primary energy price (PEP)[b] ($ per million BTU)	$\log n$ (t-3)	−0.033 (−2.995)						
Coal price/natural gas price	(t)		88774.988 (3.105)					
Electricity price/PEP	(t)					−8961.999 (−5.943)		
	(t−1)					−7664.524 (−4.751)		
Distillate fuel oil price ($ per million BTU)	(t)							−0.002 (−8.496)
LM χ^2[c]		0.656 (0.883)	0.976 (0.913)	4.959 (0.292)	2.113 (0.549)	2.373 (0.667)	2.234 (0.525)	2.375 (0.498)
LM$\chi^2(1)$[d]		1.450 (0.228)	0.564 (0.453)	0.586 (0.444)	1.709 (0.191)	1.704 (0.192)	0.403 (0.526)	0.419 (0.517)
Adjusted R^2		0.954	0.754	0.959	0.932	0.988	0.986	0.939

[a] Average energy price is a non-weigthted average of all fuel prices.
[b] Primary energy price is a non-weighted average of primary energy prices.
[c] Lagrange multiplier estimate of heteroscedasticity (Godfrey, 1978), significance level in parenthesis.
[d] Lagrange multiplier estimate of serial correlation (Breusch and Pagan, 1979), significance level in parenthesis.

We modify Jorgenson's approach by creating a physical perpetual inventory. We do this by estimating the physical size and vintage structure of the capital stock in the most recent year available, using an econometrically estimated translator of investment to actual physical changes in production capacity which is measured in tons of production capacity. Our translator does account for the lag time between the actual transaction of gross new investment expenditures and the actual change in physical capital (Jorgenson, 1971) (Table 1).

The future size and structure of the capital stock is then estimated as a function of gross new capital investments and the size of the existing physical capital stock minus the retirement of physical capital. Gross new capital investment is a function of two components, replacement investment, and expansion investment. Replacement investment is the proportion of gross new capital investment that directly replaces retired capital. We assume that capital is retired after 35 years of service. In addition, a total of 10% of gross investment is assumed to replace capital that is less than 35 years old. This fraction translates to a reduction in the size of each vintage by 0.3% of gross investment. The remaining proportion of gross investment is expansion investment, which by definition expands the capital stock and thus increases production capacity.

We econometrically estimate annual gross new capital investment from published investment rates of the pulp and paper industry (Freeman Miller, various years). The paper and paperboard investment series are deflated with the use of a capital investment deflator series provided by the Federal Reserve Bank in St. Louis (1999). The existing age structure of the physical capital stock is obtained from AF & PA(b) (various years). Separate research has been carried out to explore actual physical retirement patterns in the paper industry as a function of vintage and cost of production (Davidsdottir, 2002). In order to trace how efficiency improvements result from installation of new capital and retirement of obsolete capital we keep track of the specific capacities and efficiencies of each vintage class.

Econometric results show that annual gross new investment is influenced by production rates of 2 years earlier, and as expected, new production capacity (C_t^{N}) is directly dependent on gross new investments, lagged by 1 year (Table 1). Total capacity C_t^{total} in time period t is the sum of gross new capacity C_t^{N} and the net of total capacity C_{t-1}^{total} and retired capacity, C_{t-1}^{R}, that occurred in the previous year:

$$C_t^{\mathrm{total}} = C_t^{\mathrm{N}} + C_{t-1}^{\mathrm{total}} - C_{t-1}^{\mathrm{R}} \tag{2}$$

Here, as elsewhere in this study, model (parameter) specification and choice of lag lengths are based on conventional hypothesis tests (t and adjusted R^2) as well as econometric diagnostics such as Lagrange multiplier tests for heteroscedasticity (Breusch and Pagan, 1979) and serial correlation (Godfrey, 1978).

After establishing the vintage structure of the capital stock, vintage specific input use is estimated as a function of production rates by vintage and vintage specific input efficiencies. Consequently, the measures of gross new investment and retirement, when combined with information on the input efficiency of each vintage class and associated production rates, give a comprehensive engineering-economic description of the aggregate capital vintage structure of the industry in its relation to product markets. Changes in input efficiency and market dynamics are discussed in Section 3.2.

3.2. Production, demand, efficiency and fuel mix

We use a regression equation to estimate total US paper demand (Table 2) as a function of GDP per capita and product price. Total paper and paperboard production is in turn estimated as a function of lagged demand (Table 2), where the lag length is chosen based on econometric criteria and standard hypothesis tests. The lag captures the decision process the paper companies need to adhere to when planning for next year's production quantities.

Historical paper and paperboard production and demand data as well as data on product prices from 1970 to 1995, come from AF & PA(a) (various years), and data on real GDP (in \$1994) and population come from the Department of Commerce (various years).

Change in energy efficiency (measured in physical units per unit of output) is acquired in two steps: first, through the installation of new capital and the retirement of existing, less efficient capital and, second, through the changed efficiency of existing capital through, e.g. improved housekeeping practices. The end result of these two steps, in general, gradually increases the overall energy efficiency of the industry. Data on energy efficiency of new and old capital is available from AF & PA(a) (various years), Energetics (1990), Gilbreath et al. (1995) and EIA (1998).

To determine the efficiency of new capital, we follow the methodology used in the Industrial Module of the National Energy Modeling System (IM-NEMS) which is an energy use forecasting model used and maintained by the US Energy Information Administration (EIA, 1998). Specifically, we assume that the initial efficiency of each age class (efficiency of new capital) is a function of the aggregate average efficiency of the existing capital stock at the year of installation (E_{a-1}) and a constant relative energy intensity (REI) of new to old capital.

$$E_a = \mathrm{REI} \times \frac{\sum_{a=1}^{35} E_{a-1}}{35} \tag{3}$$

A change in the REI only influences the vintage added to the capital stock the year the change occurred and onwards from thereon. The efficiency of new capital gives a measure of the total weighted efficiency of the capital stock at the time of installation of each vintage (WE_t^N) weighted by each vintage share of total production (q_{ta}/Q_{tS}).

$$WE_t^N = \sum_{a=1}^{35} E_a \times \left(\frac{q_{ta}}{Q_{tS}}\right) \quad (4)$$

Where Q_{tS} is the total production per year, E_a is the energy efficiency of new capital, and a is the age class or vintage.

To determine changes in energy efficiency of existing capital we estimate learning curves that relate weighted average energy efficiencies of the capital stock (WE_t^O) to cumulative production (X_t) and lagged energy prices (P_{t-n}). Cumulative production is used as an indicator of experience (Yelle, 1979; Ruth, 1993). Lagged energy prices are used to capture the delayed impacts that market signals have on housekeeping practices (Table 2).

$$WE_t^O = f(X_t,\ P_{t-n}) \quad (5)$$

We assume that the rate of change in the energy efficiency of the existing capital stock is uniform across vintages. That is, the efficiency of 10-year-old capital changes as fast as the efficiency of 20-year-old capital. This assumption is made out of lack of data for capturing the actual rate of change by vintage. Theoretical studies have shown that generally the rate increases slowly up to vintages of 5–7 years of age and then declines after that (Mulder et al., 2001). Separate research has been carried out to explore specifically learning curves for already installed capital or "existing" capital in the industry (Davidsdottir, 2002). Over time, the efficiency of the existing capital stock changes as a function of age and input prices and thus the two impacts on aggregate weighted efficiency are combined using the following equations:

$$\mathrm{diff}_t = ((WE_{t-1}^O - WE_t^O)/WE_{t-1}^O) - ((WE_{t-1}^N - WE_t^N)/WE_{t-1}^N) \quad (6)$$

$$WE_t = (1 - \mathrm{diff}_t) \times WE_t^N \quad (7)$$

Where diff_t is the difference in the rate of change between changes in the total capital stock, both due to the investment in new capital and changes due to, e.g. improved housekeeping practices ($(WE_{t-1}^O - WE_t^O)/WE_{t-1}^O$), and changes in the efficiency of the total capital stock only due to the investment in new, more efficient capital ($(WE_{t-1}^N - WE_t^N)/WE_{t-1}^N$). WE_t is the total weighted average energy efficiency of the capital stock, and includes changes in the efficiency of both new and existing capital.

Following Chern and Just (1980) we use seemingly unrelated regressions (Zellner, 1962) to determine the fractional share of each fuel used in the industry. The use of a seemingly unrelated regression system enables us to explicitly take into account the potential for fuel substitution. The share of each fuel (E_t^e) of type e ($e = 1 \ldots 7$) in year t is a function of relative and absolute fuel prices in lagged and simultaneous form ($P^e_{t\,\mathrm{and}\,t-x}$) and of production levels (Q_t). Again, lagged responses capture the inertia in the system, where the industry cannot always instantly switch from one fuel to another. Contracts with fuel companies are made 6 months to a year in advance and some changes require modifications in boilers. Regression results are listed in Table 2. Historical fuel prices, on which these results are based, have been obtained from EIA (various years). Data on total energy use is from AF & PA(b) (various years).

The opportunity cost of chemicals and wastes for self-generation are assumed negligible because of high transport cost of the chemicals and wastes. In contrast, the opportunity cost of the capital for self-generation is not zero. Unfortunately, little information is available to reliably quantify capital cost of self-generation on an industry-wide basis, and we assume that the price of self-generated energy is zero. As a result of this assumption, we are likely to overestimate the rate of expansion of self-generation.

4. Scenario analysis

Section 3 summarizes relationships among changes in per capita GDP, production rates, capital turnover, capacity, efficiency, and fuel mix. These relationships provide the basis for the econometric estimation and for the specification of the dynamic computer model of the industry's market dynamics, capital stock characteristics, and carbon emissions. The model is used to explore implications of policy interventions for the industry's energy use and carbon emission profiles. Its structure is shown in Fig. 2.

The "medium population growth rate" as published by US Department of Commerce (1999) and a 1.9% annual rate of increase in GDP as used in the medium growth scenario in EIA (1999) are used to drive paper demand. To ensure consistency with the forecasted population and economic growth rates corresponding energy price forecasts until 2020 are derived from EIA (1999) to drive the product price and energy efficiency equations. Product price is assumed to grow at an annual base rate of 0.3%, though this rate varies depending on changes in energy cost of production. As estimated by Kaltenberg (1983), we use an elasticity of 0.2 as the product price impact from energy expenditures per ton of output, in addition to the already assumed 0.3% change per year. Consequently, product prices are on average increasing but changes in energy costs either facilitate smaller or a larger change per year. This means that ceteris paribus if energy expenditures decline, e.g. due to a technological breakthrough, product prices may decline as well which in turn increases demand and production levels (Table 1).

Fuel-specific carbon coefficients are used to convert information on fuel use into tons of carbon emitted by the industry (Table 3). Since an increase in (purchased) electricity use by the industry would appear as a reduction in carbon emissions, we keep track of the carbon emitted from electricity production when estimating the industry total. Fuel mix data for the electricity sector comes from EIA (1999) and we assume that the electricity purchased by the US Pulp

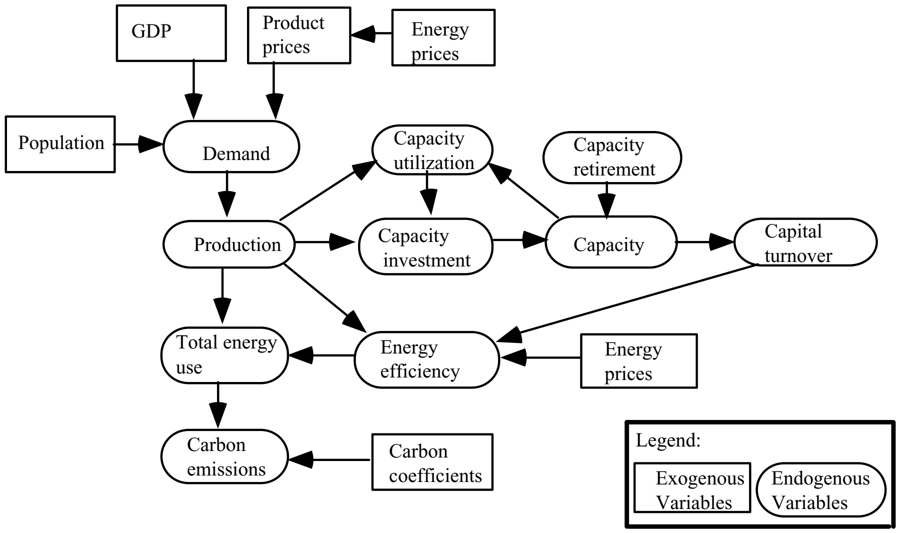

Fig. 2. Model structure.

and Paper Industry is generated at the US average fuel mix in electricity production.

We run the simulation model with historic time series data for GDP, population and energy prices. The equations presented in Tables 1 and 2 were those for which econometric test criteria were satisfied and for which historic system performance was best mimicked. For example, given the model's specification, the mean square error of simulated versus actual energy use by fuel type is less than 2%. Varying the estimated parameters (in Tables 1 and 2) within their respective confidence intervals changes the actual numerical results but the observed trends and our qualitative conclusions about the effects of alternative policies remain unaffected. Also, the actual numerical results of the model are of course sensitive to the exogenous parameters, such as GDP growth rates and energy prices (see regression results in Tables 1 and 2). However, the price and GDP forecasts that are used in the model are both derived from NEMS scenarios to achieve consistency. Varying the rate of change in those exogenous parameters will modify the trends seen in the base scenario (e.g. an increase in GDP growth results in an increase in paper demand and thus higher growth rates), yet such a change will not change the qualitative conclusions about the various policies.

Table 3
Carbon content of fuels (*Source:* EIA, 1994)

Fuel type	Metric tons of carbon per billion BTU (1994 value)
Coal	25.61
Coal (electricity generation)	25.71
Natural gas	14.47
Residual fuel oil	21.49
Oil (electricity generation)	19.95
Liquid petroleum gas	17.02
Distillate fuel oil	19.95

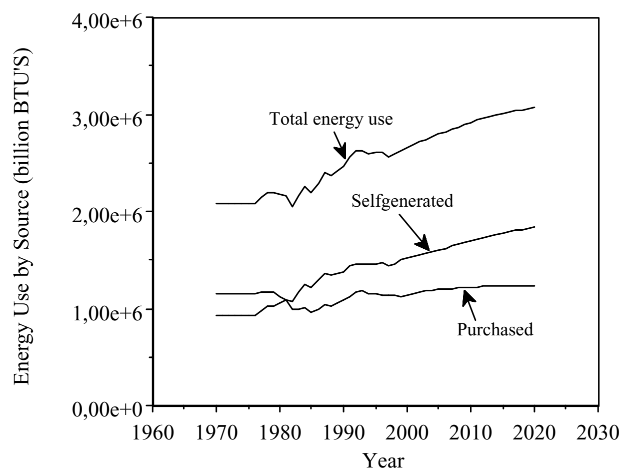

Fig. 3. Base scenario energy use by type (*source:* AF & PA(a), various years and model simulations).

4.1. *Base scenario*

Projections of GDP, population and energy prices are used to explore industry dynamics and emissions trajectories from 1998 up to the year 2020. In this base scenario, output reaches 100 million short tons[2] by 2003 and 125.6 million tons in 2020, which is the last year of simulations. This result is slightly more conservative than our earlier forecast where we showed production levels to reach 100 million tons by 2002 and to reach 129 million tons in 2020 (Ruth et al., 1998).

In the base scenario, total industrial energy use increases by 24.8% between 1990 and 2020 (Fig. 3). Over the same time frame, energy efficiency increases by 21.8% (Fig. 4). The percentage share of energy supplied through self-generation increases from 56 to 60% in 2020. Among

[2] 1 short ton = 0.9072 metric tons.

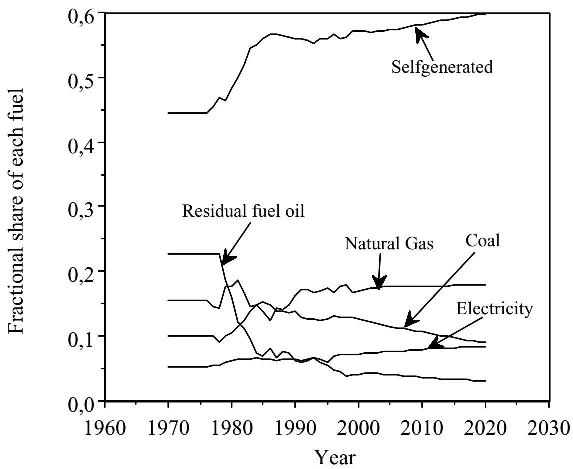

Fig. 4. Base scenario energy use per ton and carbon per ton (*source:* AF & PA(a), various years and model simulations).

purchased fuels, the use of coal is expected to decline from 14% in 1990 to 9% of total energy use in 2020. Over the same time frame the use of residual fuel oil declines from 6 to 3%. The fractional share of electricity and natural gas, in contrast, is expected to increase from 6 to 8% and 9 to 18%, respectively, between 1990 and 2020. Carbon emissions increase by 20% between 1990 and 2020 (Fig. 5). In contrast, carbon emissions per ton of output are expected to decline 24.8% over the same timeframe. This decline indicates that the rate of growth in output is faster than the rate of growth in energy use or carbon emissions.

Energy expenditures are estimated to increase from $4.4 in 1990 to $4.9 billion in 2020. Over the same timeframe energy expenditures per ton of output are expected to decline from $54.1 to $39.1 per ton of output. All monetary units are in constant $1994.

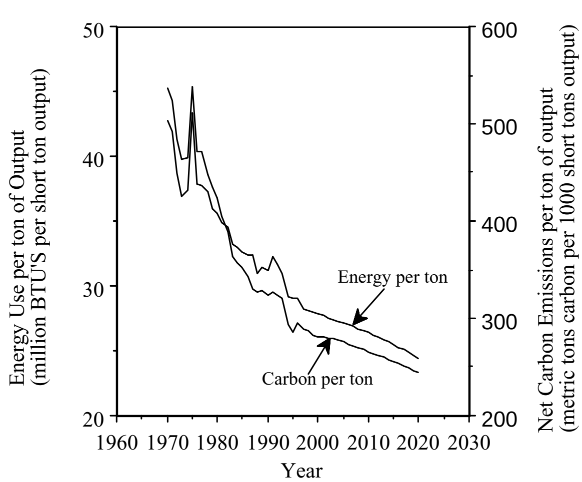

Fig. 5. Base scenario fractional share of each fuel (*source:* AF & PA(a), various years and model simulations).

4.2. Policy scenarios

To simulate the impact of different climate change policies on energy use and carbon emissions we examine four policy scenarios to which we compare the base scenario. We assume that each policy is implemented in the year 2004. We ensure comparability among the four scenarios by choosing policies that lead to the same amount of cumulative carbon emissions as estimated between 2000 and 2020, and the same cumulative amount of prevented carbon emissions between 2000 and 2020, as results from a $75 increase in the cost of carbon. The four policies are:

- An increase of $75 per ton C in cost of carbon. This scenario is called *$75 per ton carbon scenario*.
- An energy tax of 71.7%. This scenario is called *71.7% energy tax*.
- A decline from 85.0 to 46.0% in energy intensity of new capital relative to the aggregate energy intensity of existing capital. This could be achieved by supporting the diffusion of energy efficient technologies by facilitating investment, e.g. through low cost and guaranteed loans and accelerated depreciation schedules. A switch to black liquor gasification would go a long way towards reaching this goal since that switch alone would increase the energy efficiency of chemical pulping by 23% (Martin et al., 2000). This scenario is called *REI*.
- A combination of a decline in energy intensity of new capital and an increase in the cost of carbon a scenario we call *smart policy*. The cost of carbon in the smart policy scenario is $25 per ton C and the corresponding relative energy intensity that yields the same carbon emissions in 2020 as a $75 per ton C increase in cost of carbon is 59.4%.

Detailed results of the four policy scenarios and the base scenario are presented in Table 4. For example, the cost of carbon policy has the largest impact on production levels leading to 0.6% lower output in 2020 than observed in the base scenario. The energy tax reduces production levels 0.5% below base scenario production levels in 2020. In contrast, in the smart policy and the REI scenario production increases by 0.1 and 0.2%, respectively, when compared to the base scenario. This is due to declining energy costs hence lower prices for paper products and thus increased demand.

Energy use is increasing but at a declining rate, and in the REI scenario, energy use in 2020 is indeed lower than in 1990 (Fig. 6). The cost of carbon scenario reduces energy use the least, when compared to other policy options. This is because the cost of carbon policy stimulates fuel switching, and thus reducing carbon emissions does not necessitate as large of a decrease in total energy use.

Energy use per ton of output declines substantially more in the policy scenarios than in the base scenario (Fig. 7). Energy use per ton of output is 1.4% lower in 2020 in the cost of carbon scenario when compared to the base scenario, 5.7% lower in the energy tax scenario, 17.3% lower in the relative

Table 4
Summary of model results

		Base scenario	$75 per ton carbon	71.7% energy tax	REI 0.460	Smart policy
Total production (fractional change from 1990 levels to 2020)		0.596	0.590	0.591	0.598	0.597
Total energy use (fractional change from 1990 levels to 2020)		0.248	0.225	0.157	−0.027	0.062
Total purchased fuel use (fractional change from 1990 levels to 2020)		0.136	0.045	−0.031	−0.119	−0.055
Total self-generated energy (fractional change from 1990 levels to 2020)		0.336	0.367	0.306	0.046	0.155
Energy intensity, energy use/output (fractional change from 1990 levels to 2020)		−0.218	−0.232	−0.275	−0.391	−0.335
Years gained in efficiency improvement		0	3	7	10	9
Net carbon emissions (fractional change from 1990 levels to 2020)		0.200	0.073	0.034	−0.061	−0.012
Net carbon emissions per ton of output (fractional change from 1990 levels to 2020)		−0.248	−0.327	−0.352	−0.412	−0.381
Energy mix						
Coal (% share of total energy use)	1990, 2020	0.14, 0.09	0.14, 0.05	0.14, 0.09	0.14, 0.09	0.14, 0.07
Residual fuel oil (% share of total energy use)	1990, 2020	0.06, 0.03	0.06, 0.01	0.06, 0.01	0.06, 0.03	0.06, 0.02
Electricity (% share of total energy use)	1990, 2020	0.06, 0.08	0.06, 0.09	0.06, 0.08	0.06, 0.09	0.06, 0.09
Natural gas (% share of total energy use)	1990, 2020	0.09, 0.18	0.09, 0.21	0.09, 0.18	0.09, 0.18	0.09, 0.20
Self-generated energy (% share of total energy use)	1990, 2020	0.56, 0.60	0.56, 0.62	0.56, 0.63	0.56, 0.60	0.56, 0.61
Financial parameters						
Cumulative present value of energy expenditures, 2000–2020 (billion $1994, 5% discount rate)		48.461	62.197	67.616	45.952	51.636
Cumulative present value of cost of carbon payments, 2000–2020 (billion $1994, 5% discount rate)		0	14.079	21.722	0	4.720
Energy cost per unit of output in 2020 ($1994 per short ton output)		39.08	38.17	33.81	30.53	33.49

energy intensity scenario and is 11.7% lower in the smart policy scenario. Again, the difference between the scenarios is explained by the fact that an increase in the cost of carbon facilitates a shift towards less carbon intensive fuels but an energy tax or the REI policy does not. Consequently, to reach the same level of cumulative carbon emissions as is reached in the cost of carbon scenario the other policies must reduce energy use per ton of output to a larger extent and hence total energy use follows the same trend. The actual numerical results of energy intensity changes indicate that our estimate of energy intensity in the base scenario is as expected higher

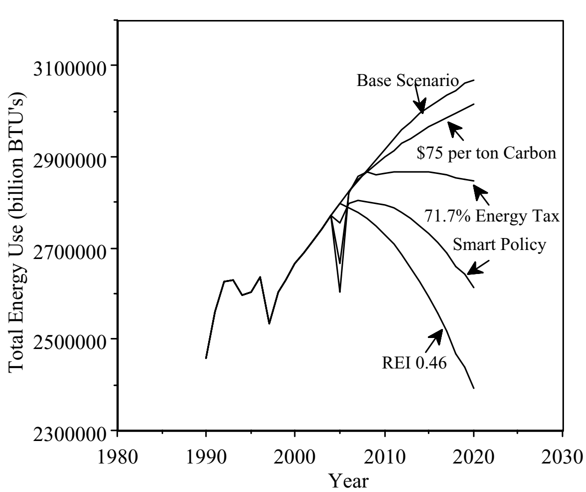

Fig. 6. Total energy use with and without climate change policies (*source*: AF & PA(a), various years and model simulations).

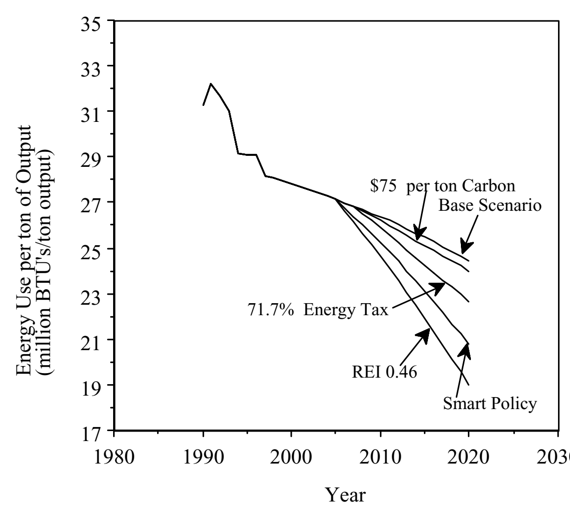

Fig. 7. Total energy use per ton of output with and without climate change policies (*source:* AF & PA(a), various years and model simulations).

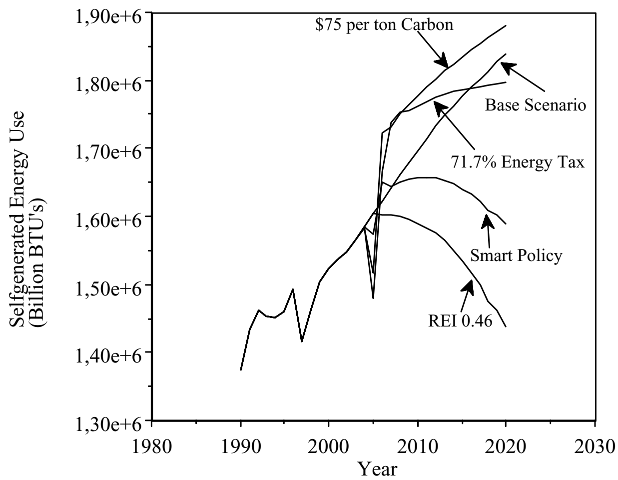

Fig. 8. Self-generated energy use with and without climate change policies (*source:* AF & PA(a), various years and model simulations).

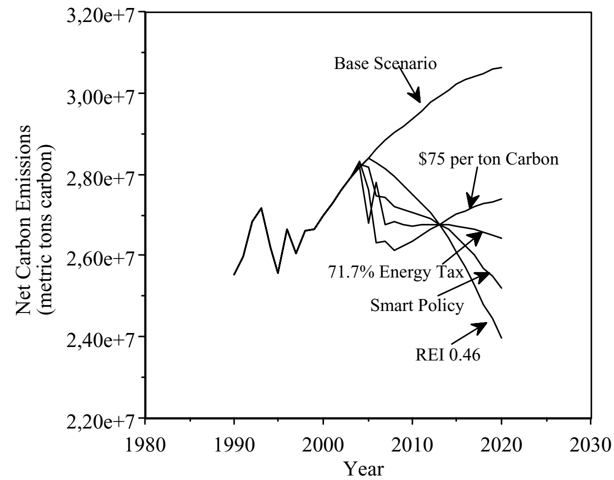

Fig. 10. Net carbon emissions with and without climate change policies (*source:* AF & PA(a), various years and model simulations).

than in business as usual scenarios of bottom up studies (e.g. Energetics, 1990). Also, the results in the smart policy scenario and the REI scenario, or approximately 20 and 19 million BTU's per ton of output, respectively, are slightly higher than a penetration of 100% advanced technologies which result in an aggregate intensity of approximately 18 million BTU's per ton of output (Energetics, 1990).

Three of the four policies cause a change in the mix of energy use in the industry (Figs. 8 and 9). An increase in the cost of carbon results in a shift towards selfgenerated energy and natural gas away from coal and residual fuel oil. An energy tax only facilitates a shift towards increased use of self-generated fuels, and away from residual fuel oil, but otherwise does not significantly alter the fuel shares. A change in the relative energy intensity does, by itself, not influence the energy mix in the industry and the result of the smart policy scenario falls between the increased cost of carbon scenario and the relative energy intensity scenario.

Carbon emissions will be lower in all policy scenarios when compared to the base scenario. In the REI and smart policy scenarios, net carbon emissions are even seen to be below 1990 levels and declining (Fig. 10). Carbon emissions per ton are in all policy scenarios lower than in the base scenario, where again the REI and the smart policy are the most effective at reducing emissions (Fig. 11). When compared to the base scenario, energy cost per ton of output in 2020 is expected to decline from $39.1 per ton of output in the base scenario to $38.17 in the carbon tax scenario, to $33.81 in the energy tax scenario, to $33.49 in the smart policy scenario and $30.53 in the relative energy intensity scenario (Table 4). This amounts to energy cost savings per ton in 2020 of $8.57 per ton of output or $1.07 billion given an output of 125 million tons in the REI scenario, money that could be used to invest and develop more efficient technologies. Conversely, one could argue that industry would

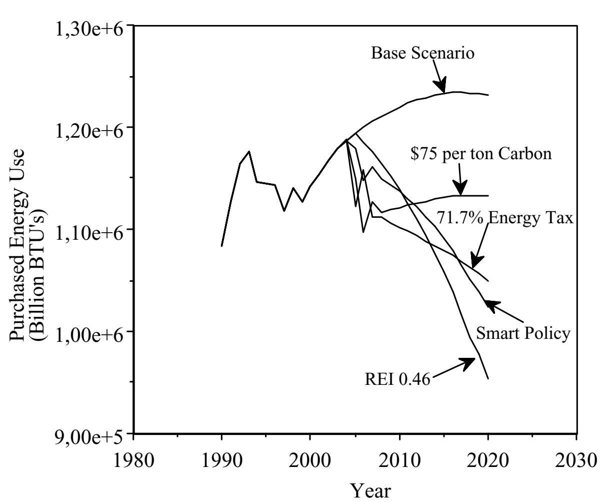

Fig. 9. Purchased energy use with and without climate change policies (*source:* AF & PA(a), various years and model simulations).

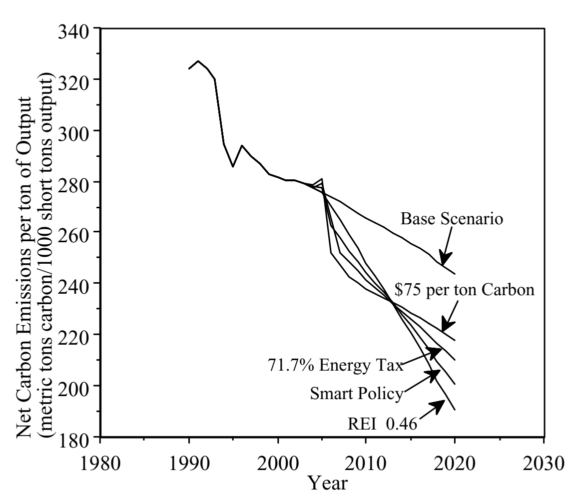

Fig. 11. Net carbon emissions per ton of output with and without climate change policies (*source:* AF & PA(a), various years and model simulations).

(ceteris paribus) be willing to forego up to $1.07 billion for investments in improved REI.

The investment cost of the three policy options is not estimated except through tax revenues. Since an energy tax does not facilitate fuel switching, the tax penalty facing the industry to reach the same amount of total carbon abated in 2020, as an increase in the cost of carbon, would be 33% higher (Table 4).

5. Discussion and conclusions

Climate change policies such as an increase in the cost of carbon and energy taxes have commonly been proposed as tools to reduce carbon emissions from industrial processes. Previous analyses of the US Pulp and Paper Industry have been either strongly top–down or bottom–up, have paid little tribute to the capital vintage structure of the industry, and have rarely explored combinations of policy tools to influence an industry's potential for efficiency improvements, such as a combination of cost of carbon policies to stimulate changes in fuel mix and existing capital with policies that accelerate changes in aggregate efficiencies by promoting adoption of highly efficient equipment.

The model presented in this paper does address those issues. Specifically, we provide an application of capital vintage analysis and modeling to a specific industry in order to more adequately capture industrial capital dynamics and their associated energy use and carbon emission profiles. Such an application carried out here for the US Pulp and Paper Industry has long been called for in the scientific literature. However, while vintage-specific capacity, energy use and carbon emissions are reflected with great detail in the model and quantified on the basis of engineering and econometric analyses, various constraints had to be imposed on the boundaries for our analysis. For example, we did not explore impacts of climate change policies on the rest of the economy or world, and how these may feed back to affect investment and material and energy use by the US Pulp and Paper Industry.

These limitations aside, our results demonstrate that a combination of different policies, such as an increase in the cost of carbon and an incentive for the industry to invest in more efficient new capital could be quite successful in stimulating a reduction in carbon emissions by leveraging tendencies of the industry to change its fuel mix and improve efficiencies. While a technology standard or energy tax, if applied all by themselves, will gradually increase energy efficiency, they will not stimulate fuel switching between purchased fuels. To reach the same total reduction in carbon emissions, the tax revenue (and thus the tax penalty on the industry) will be considerably higher for a pure energy tax than, e.g. if the tax rate is tied to the carbon content of purchased fuels. Similarly, it is unlikely that an increase in the cost of carbon or energy taxes will permanently increase the industry's aggregate energy efficiency since energy cost is not seen to have significant impact on gross investment and thus on the turnover rate of capital. The reason for this is three-fold. First, energy expenditures are a small proportion of the total production cost, which is dominated by fiber inputs. Second, the cost of installing, e.g. new, more efficient recovery boilers using black liquor gasification is much higher than the energy savings gained, where the cost is estimated at $70 million for a pulping capacity of 350 000 tons per year (Hekkert and Worrell, 1997). Third, the industry requires a maximum of three year payback period on energy saving equipment. Given those three issues it is not surprising that investments in energy saving equipment are often a side-bonus to other investments in the industry, e.g. to capacity expansion. Hence, purely price-based policies such as energy taxes or an increase in the cost of carbon may fall short in affecting the evolution of the capital stock towards increased efficiency they only stimulate changes within the limits of the existing stock and as a consequence are bound to appear as a drag on GDP. In contrast, our results indicate that a combination of cost of carbon increases with policies that provide incentives that advance adoption of higher efficiency technology will significantly stimulate a slowdown in carbon emissions rates from pulp and paper production while reducing impacts on productivity of the industry. Such incentive providing policies include voluntary sector agreements (e.g. climate wise in the United States) in addition to investment tax rebates and subsides for investment in energy-efficient technologies to name a few (Worrell et al., 2001).

Comparisons across industries reveals that the cost of carbon and capital oriented policies have vastly different implications for energy use and carbon emissions profiles (Ruth et al., 2004). These differences are largely attributable to each industry's production and capital vintage structure that greatly limits the potential for change. This implies that the same policy instrument may trigger different kinds of responses by different industries. For instance a change in the cost of carbon will in the Iron and Steel Industry result in shifting production among segments in the industry to changing the fuel mix in the pulp and paper industry to changing the use of intermediate products in ethylene production (Ruth et al., 2004). Thus, various instruments have different abilities to leverage opportunities in industry to achieve desired policy goals, but for most industries a mix of policy instruments is the most useful to improve simultaneously different industry features. Yet, for all the capital and energy intensive industries, which most seem to experience considerable capital stock inertia, simply raising the cost of carbon is not sufficient to overcome capital vintage effects (Ruth et al., 2004).

An international comparison for the paper industry reveals that the impact of different polices varies with capital vintage and production structure, resource endowments for the industry such as access to waste or virgin fibers and the extent and potential for energy self-generation. For instance, if an industry does not have notable opportunities for energy self-generation an increase in energy prices as a result of increased cost of carbon or energy taxes, is likely to reduce production levels and increase energy efficiency more than if the industry was able to shift over to increased self-generation. However, regardless of location, resource availability and production structure, an increase in the rate of capital turnover is the most important factor in permanently changing carbon emission profiles and energy efficiency in the pulp and paper industry (see for, e.g. Nystrom and Cornland, 2003).

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