Motivation (I)

- Consensus about climate change due greenhouse gas emissions.
But also increasing recognition that most of the action will come to transition to clean technology.

How to switch to clean technology in the best (welfare maximizing)
Empirical work: possible switch away from dirty to clean technologies in response to changes in prices and policies.

- Newell, Jaffe and Stavins (1999):
  - following the oil price hikes, innovation in air-conditioners towards more energy efficient units

- Popp (2002):
  - higher energy prices associated with a significant increase in energy-saving innovations

- Hassler, Krusell and Olovsson (2011):
  - trend break in energy-saving factor productivities after high oil prices

- Aghion et al. (2012):
  - significant impact of carbon taxes on the direction of innovation in the automobile industry.
Motivation (III)

- A systematic investigation necessitates:
  - micro model
    - with carbon emissions and potential climate change,
    - where clean and dirty technologies compete, and
    - research incentives (and the direction of technological change) are endogenous.
  - micro data
    - for the modeling of competition in production and innovation,
  - quantitative analysis
    - to study the impacts of various policies.

- This lecture: two models—first about the conceptual issues (less micro and no data) and the second more about micro structure of technology choices, estimation and quantitative analysis.
Exogenous Growth Approaches

- Economic analyses using computable general equilibrium models with exogenous technology (and climatological constraints; e.g., Nordhaus, 1994, 2002).

- Key issues for economic analyses: (1) economic costs and benefits of environmental policy; (2) costs of delaying intervention (3) role of discounting and risk aversion.

- Various conclusions:
  1. **Nordhaus approach**: intervention should be limited and gradual; small long-run growth costs.
  2. **Stern/Al Gore approach**: intervention needs to be large, immediate and maintained permanently; large long-run growth costs.
  3. **Greenpeace approach**: only way to avoid disaster is zero growth.
Endogenous and directed technology

Very different answers are possible.

1. Immediate and decisive intervention is necessary (in contrast to Nordhaus)
2. Temporary intervention may be sufficient (in contrast to Stern/Al Gore)
3. Long-run growth costs may actually be very limited (in contrast to all of them).
4. Two instruments—not one—necessary for optimal environmental regulation.
Why?

- Two sector model with “clean” and “dirty” inputs with two key externalities
- *Environmental externality*: production of dirty inputs creates environmental degradation.
- Researchers work to improve the technology depending on expected profits and “**build on the shoulders of giants in their own sector**”.
  - *Knowledge externality*: advances in dirty (clean) inputs make their future use more profitable.
- Policy interventions can **redirect technological change** towards clean technologies.
Why? (Continued)

1. Immediate and decisive intervention is necessary (in contrast to Nordhaus)
   → without intervention, innovation is directed towards dirty sectors; thus gap between clean and dirty technology widens; thus cost of intervention (reduced growth when clean technologies catch up with dirty ones) increases

2. Temporary intervention may be sufficient (in contrast to Stern/Al Gore), long-run growth costs limited (in contrast to all of them)
   → once government intervention has induced a technological lead in clean technologies, firms will spontaneously innovate in clean technologies (if clean and dirty inputs are sufficiently substitutes).

3. Two instruments, not one:
   → optimal policy involves both a carbon tax and a subsidy to clean research to redirect innovation to green technologies
   → too costly in terms of foregone short-run consumption to use carbon tax alone
Model (1): production

- Infinite horizon in discrete time (suppress time dependence for now)
- Final good $Y$ produced competitively with a clean intermediary input $Y_c$, and a dirty input $Y_d$

$$Y = \left( Y_c^{\frac{\varepsilon-1}{\varepsilon}} + Y_d^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

- Most of the analysis: $\varepsilon > 1$, the two inputs are substitute.
- For $j \in \{c, d\}$, input $Y_j$ produced with labor $L_j$ and a continuum of machines $x_{ji}$:

$$Y_j = L_j^{1-\alpha} \int_0^1 A_j^{1-\alpha} x_{ji}^\alpha \, di$$

- Machines produced \textit{monopolistically} using the final good
Model (2): consumption

- Constant mass 1 of infinitely lived representative consumers with intertemporal utility:

\[ \sum_{t=0}^{\infty} \frac{1}{(1 + \rho)^t} u(C_t, S_t) \]

where \( u \) increasing and concave, with

\[ \lim_{S \to 0} u(C, S) = -\infty; \frac{\partial u}{\partial S}(C, \bar{S}) = 0 \]
Model (3): environment

- Production of dirty input depletes environmental stock $S$:
  \[
  S_{t+1} = -\xi Y_{dt} + (1 + \delta) S_t \quad \text{if} \quad S \in (0, \bar{S}).
  \]  

- Reflecting at the upper bound $\bar{S} (< \infty)$: baseline (unpolluted) level of environmental quality.
- Absorbing at the lower bound $S = 0$.
- $\delta > 0$: rate of “environmental regeneration” (measures amount of pollution that can be absorbed without extreme adverse consequences)
- $S$ is general quality of environment, inversely related to CO2 concentration (what we do below for calibration).
Model (4): innovation

- At the beginning of every period scientists (of mass $s = 1$) work either to innovate in the clean or the dirty sector.
- Given sector choice, each randomly allocated to one machine in their target sector.
- Every scientist has a probability $\eta_j$ of success (without congestion).
  - if successful, proportional improvement in quality by $\gamma > 0$ and the scientist gets monopoly rights for one period, thus
    \[ A_{jit} = (1 + \gamma) A_{jit-1}; \]
  - if not successful, no improvement and monopoly rights in that machine randomly allocated to an entrepreneur who uses technology
    \[ A_{jit} = A_{jit-1}. \]
- simplifying assumption, mimicking structure in continuous time models.
Model (5): innovation (continued)

- Therefore, law of motion of quality of input in sector $j \in \{c, d\}$ is:

  $$A_{jt} = \left( 1 + \gamma \eta_j s_j \right) A_{jt-1}$$

- **Note:** knowledge externality; “building on the shoulders of giants,” but importantly “in own sector”

  - Intuition: Fuel technology improvements do not directly facilitate discovery of alternative energy sources

Assumption

$A_{d0}$ sufficiently higher than $A_{c0}$.

- Capturing the fact that currently fossil-fuel technologies are more advanced than alternative energy/clean technologies.
Laissez-faire equilibrium: direction of innovation

Scientists choose the sector with higher expected profits $\Pi_{jt}$:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d} \left( \frac{p_{ct}}{p_{dt}} \right)^{\frac{1}{1-\alpha}}$$

- The direct productivity effect pushes towards innovation in the more advanced sector.
- The price effect towards the less advanced, price effect stronger when $\varepsilon$ smaller.
- The market size effect towards the more advanced when $\varepsilon > 1$. 
Laissez-faire equilibrium (continued)

- Use equilibrium machine demands and prices in terms of technology levels (state variables) and let $\varphi \equiv (1 - \alpha)(1 - \varepsilon) \ (< 0$ if $\varepsilon > 1)$:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d} \left( \frac{1 + \gamma \eta_c s_{ct}}{1 + \gamma \eta_d s_{dt}} \right)^{-\varphi - 1} \left( \frac{A_{ct-1}}{A_{dt-1}} \right)^{-\varphi}.$$

- Implications: innovation in relatively advanced sector if $\varepsilon > 1$
Laissez-faire equilibrium production levels

- Equilibrium input production levels

\[ Y_d = \left( \frac{1}{(A_c^\phi + A_d^\phi)^{\frac{\alpha + \phi}{\phi}}} \right)^{\alpha+\phi} A_d^\alpha A_c^\phi; \]

\[ Y = \frac{A_c A_d}{(A_c^\phi + A_d^\phi)^{\frac{1}{\phi}}} \]

- Recall that \( \phi \equiv (1 - \alpha)(1 - \varepsilon) \).

- In particular, given the assumption that \( A_{d0} \) sufficiently higher than \( A_{c0} \), \( Y_d \) will always grow without bound under laissez-faire
  - If \( \varepsilon > 1 \), then all scientists directed at dirty technologies, thus
    \[ gY_d \rightarrow \gamma \eta_d \]
Environmental disaster

- An environmental “disaster” occurs if $S_t$ reaches 0 in finite time.

Proposition

Disaster.

The laissez-faire equilibrium always leads to an environmental disaster.

Proposition

The role of policy.

1. when the two inputs are strong substitutes ($\epsilon > 1 / (1 - \alpha)$) and $\bar{S}$ is sufficiently high, a temporary clean research subsidy will prevent an environmental disaster;

2. in contrast, when the two inputs are weak substitutes ($\epsilon < 1 / (1 - \alpha)$), a temporary clean research subsidy cannot prevent an environmental disaster.
Sketch of proof

- Look at effect of a temporary clean research subsidy
- Key role: **redirecting technological change**; innovation can be redirected towards clean technology
- If $\varepsilon > 1$, then subsequent to an extended period of taxation, innovation will remain in clean technology
- Is this sufficient to prevent an environmental disaster?
Sketch of proof (continued)

- Even with innovation only in the clean sector, production of dirty inputs may increase
  - *on the one hand*: innovation in clean technology reduces labor allocated to dirty input \( \Rightarrow Y_d \downarrow \)
  - *on the other hand*: innovation in clean technology makes final good cheaper an input to production of dirty input \( \Rightarrow Y_d \uparrow \)
  - which of these two effects dominates, will depend upon \( \varepsilon \).

- With clean research subsidy (because \( \varepsilon > 1 \) and thus \( \varphi < 0 \)):
  \[
  Y_d = \frac{1}{(A_c^\varphi + A_d^\varphi)^{\frac{\alpha + \varphi}{\varphi}}} A_c^{\alpha + \varphi} A_d \rightarrow A_c^{\alpha + \varphi}
  \]

- If \( \alpha + \varphi > 0 \) or \( \varepsilon < 1/(1 - \alpha) \), then second effect dominates, and long run growth rate of dirty input is positive equal to \( (1 + \gamma \eta_c)^{\alpha + \varphi} - 1 \)
- If \( \alpha + \varphi < 0 \) or \( \varepsilon > 1/(1 - \alpha) \), then first effect dominates, so that \( Y_d \) decreases over time.
Cost of intervention and delay

- Concentrate on strong substitutability case \((\varepsilon > 1/ (1 - \alpha))\)
- While \(A_{ct}\) catches up with \(A_{dt}\), growth is reduced.
- \(T\): number of periods necessary for the economy under the policy intervention to reach the same level of output as it would have done within one period without intervention.
- If intervention delayed, not only the environment gets further degraded, but also technology gap \(A_{dt-1}/A_{ct-1}\) increases, growth is reduced for a longer period.
Complementary case

- Suppose instead that clean and dirty inputs are complements, i.e., \( \varepsilon < 1 \).
- Innovation is directed towards the more backward sector
  - price effect dominates the direct productivity effect and market size effect now favors innovation in the more backward sector
  - typically innovation first occurs in clean, then in both, asymptotically balanced between the two sectors.
- Asymptotic growth rate of dirty input:
  \[
  g_{Y_d} \rightarrow \gamma \eta_c \eta_d / (\eta_c + \eta_d) < \gamma \eta_d \ (\text{growth rate in substitute case})
  \]
  disaster occurs sooner than in the substitute case.
- ... but it is unavoidable using only a temporary clean research subsidy.
  - If the clean sector is the more advanced, innovation will take place in dirty once the subsidy is removed, and long-run growth rate of dirty input remains the same.
Undirected technical change

- Compare with a model where scientists randomly allocated across sectors so as to ensure equal growth in the qualities of clean and dirty machines, thus $g_{Yd} \rightarrow \gamma \eta_c \eta_d / (\eta_c + \eta_d) < \gamma \eta_d$

Proposition

The role of directed technical change.

When $\varepsilon > 1 / (1 - \alpha)$:

1. An environmental disaster under laissez-faire arises earlier with directed technical change than in the equivalent economy with undirected technical change.

2. However, a temporary clean research subsidy can prevent an environmental disaster with directed technical change, but not in the equivalent economy with undirected technical change.
Proposition

Optimal environmental regulation.  
The social planner can implement the social optimum through a "carbon tax" on the use of the dirty input, a clean research subsidy and a subsidy for the use of all machines (all taxes/subsidies are financed lump sum).

1. If $\varepsilon > 1$ and the discount rate $\rho$ is sufficiently small, then in finite time innovation ends up occurring only in the clean sector, the economy grows at rate $\gamma \eta_c$ and the optimal subsidy to clean research, $q_t$, is temporary.

2. The optimal carbon tax, $\tau_t$, is temporary if $\varepsilon > 1/(1 - \alpha)$ but not if $1 < \varepsilon < 1/(1 - \alpha)$.

Interpretation.
Carbon tax

- Optimal carbon tax schedule is given by

\[ \tau_t = \frac{\omega_{t+1} \xi}{\lambda_t p dt}, \]

- \( \lambda_t \) is the marginal utility of a unit of consumption at time \( t \)
- \( \omega_{t+1} \) is the shadow value of one unit of environmental quality at time \( t + 1 \), equal to the discounted marginal utility of environmental quality as of period \( t + 1 \)

- If \( \varepsilon > 1 / (1 - \alpha) \), dirty input production tends towards 0 and environmental quality \( S_t \) reaches \( \bar{S} \) in finite time, carbon tax becomes null in finite time.

- If gap between the two technologies is high, relying on carbon tax to redirect technical change would reduce too much consumption.
Exhaustible resources

- Polluting activities (CO2 emissions) often use an exhaustible resource (most importantly, oil).
- Dirty input produced with some exhaustible resource $R$:

\[
Y_d = R^\alpha_2 L_d^{1-\alpha} \int_0^1 A_i^{1-\alpha_1} x_i^{\alpha_1} di,
\]

with $\alpha_1 + \alpha_2 = \alpha$.
- The resource stock $Q_t$ evolves according to

\[
Q_{t+1} = Q_t - R_t
\]

- Extracting 1 unit of resource costs $c(Q_t)$ (with $c' \leq 0$, $c(0)$ finite). As $Q_t$ decreases, extracting the resource becomes increasingly costly.
Main results

- With exhaustible resources, environmental disaster could be averted without policy intervention because increasing prices of the scarce exhaustible resources could automatically redirect technological change.

- Nevertheless, optimal policy very similar with or without exhaustible resources.
Two-country case

- Two countries: North (N), identical to the economy studied so far, and that the South (S) imitating Northern technologies.

- Thus there are two externalities:
  1. **environmental externality**: dirty input productions by both contribute to global environmental degradation

     \[ S_{t+1} = -\tilde{\xi} \left( Y_{dt}^N + Y_{dt}^S \right) + (1 + \delta) S_t \text{ for } S \in (0, \bar{S}). \]

  2. **knowledge externality**: South imitates North’s technologies

     \[ \frac{\Pi_{ct}^S}{\Pi_{dt}^S} = \frac{\kappa_c (p_{ct}^S)^{\frac{1}{1-\alpha}} L_{ct}^S A_{ct}^N}{\kappa_d (p_{dt}^S)^{\frac{1}{1-\alpha}} L_{dt}^S A_{dt}^N} \]
Main results

- Do we need global coordination to avert an environmental disasters?
  - In autarky, the answer is no because advances in the North will induce the South to also switch to clean technologies.
  - But free trade may undermine this result by creating pollution havens—the South can be encouraged to specialize even more in dirty technologies because of environmental policy in the north.
Modeling competition between clean and dirty technologies

- Now a more micro-based model of competition between clean and dirty technologies that can be estimated from firm-level data (for the energy sector in the United States) on
  - R&D expenditures,
  - patents,
  - sales,
  - employment,
  - firm entry and exit.

- Data sources:
  - Longitudinal Business Database and Economic Censuses,
  - the National Science Foundation’s Survey of Industrial R&D,
  - the NBER Patent Database.

- Also, a more realistic model of the carbon cycle.
- This will allow more systematic counterfactual policy experiments.
Preferences

- Infinite-horizon economy in continuous time.
- Representative household:

\[ U = \int_0^\infty \exp(-\rho t) \ln C_t dt. \]

- Inelastic labor supply, no occupational choice:
  - Unskilled labor: for production: measure 1, earns \( w^u_t \)
  - Skilled labor: measure \( L^s \), earns \( w^s_t \).
  - cover fixed and variable costs of R&D.

- Hence the budget constraint is

\[ C_t \leq w^u_t + L^s \cdot w^s_t + \Pi_t \]

- Closed economy and no investment, resource constraint: \( Y_t = C_t \).
Unique final good $Y_t$:

$$\ln Y_t = -\gamma (S_t - \bar{S}) + \int_0^1 \ln y_{it} di,$$

$y_{it}$: quantity of intermediate good $i$.

$S_t \geq \bar{S}$: atmospheric carbon concentration.

$\bar{S} > 0$: preindustrial level.
Intermediate Good Technology (I)

- Intermediate good $y_{it}$:

$$y_{it} = \begin{cases} 
  y_{it}^c & \text{with clean technology, or} \\
  y_{it}^d & \text{with dirty technology}
\end{cases}$$
Intermediate Good Technology (II)

- Firm $f$ can produce intermediate $i$ with either a clean or dirty, $j \in \{c, d\}$:
  \[
y^j_{it}(f) = q^j_{it}(f) l^j_{it}(f)
  \]
  - $l^j_{it}(f)$: production workers
  - $q^j_{it}(f)$: labor productivity.
- Marginal cost of production is
  \[
  MC^j_{it} = \left(1 + \tau^j_t\right) \frac{w^u_t}{q^j_{it}}
  \]
  where $\tau^j_t$ is the tax rate on technology $j$.  

Intermediate Good Technology (III)

- Produce with technology $j \in \{c, d\}$ if
  \[
  \left(1 + \tau_t^{-j}\right) \frac{w_t^u}{q_{it}^{-j}} > \left(1 + \tau_t^j\right) \frac{w_t^u}{q_{it}^j}.
  \]
- i.e., produce with dirty technology iff
  \[
  \frac{q_{it}^d}{q_{it}^c} > \frac{1 + \tau_t^d}{1 + \tau_t^c}.
  \]
Quality Ladder

- Innovations improve quality by multiples of $\lambda > 1$.
- $n_{it}^j$ improvements leads to

$$q_{it}^j = \lambda n_{it}^j,$$

where $q_{i0}^j = 1$.

- Hence

$$\frac{q_{it}^d}{q_{it}^c} = \lambda^{n_{it}}$$

$n_{it} = n_{it}^d - n_{it}^c$.

- Define $\mu_n$ : fraction of $n$-step industries.
Carbon Tax

- For tractability, tax rates are:

\[ 1 + \tau^i_t = \lambda m^i_t. \]

- Hence:

\[ \frac{1 + \tau^d_t}{1 + \tau^c_t} = \lambda m_t, \]

where \( m_t \equiv m^d_t - m^c_t \).
Production Decision

- Produce with technology $j = dirty$ if

$$\frac{q_{it}^d}{q_{it}^c} > \frac{1 + \tau_t^d}{1 + \tau_t^c}$$

- $\lambda^{n_{it}} > \lambda^{m_{it}}$

- $n_{it} > m_t$. 
Production Decision

- Alternatively, produce with technology $j = \text{dirty}$ if:

$$\frac{q_{it}^d}{q_{it}^c} > \frac{1 + \tau_t^d}{1 + \tau_t^c} \iff \frac{q_{it}^d}{1 + \tau_t^d} > \frac{q_{it}^c}{1 + \tau_t^c}$$

i.e., compare tax-adjusted productivities.
Innovation, the Quality Ladder and Dynamics

\[ \frac{q^j}{1 + \tau^j} \]

Tax adjusted productivity

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Firms and R&D (I)

- Firm $f$: collection of leading-edge technologies (Klette & Kortum, 2004).
- $u_{ft}^j$: # of leading-edge technologies.
- Poisson flow rate of $X_t^j$ innovations:
  \[ X_t^j = \theta \left( H_t^j \right)^\eta \left( u_t^j \right)^{1-\eta}, \]
  - $H_t^j$: number of scientists
  - $\eta \in (0, 1)$, and $\theta > 0$.
- Fixed R&D cost of $u_tF_l$ scientists for operation.
Firms and R&D (II)

- Total cost:

$$C_t (u_t, x_t^j) = (1 - s_{lt}^j) w_t^s u_t \left[ (x_t^j)^{\frac{1}{\eta}} \theta^{-\frac{1}{\eta}} + F_I \right],$$

where:

- $x_t^j \equiv X_t^j / u_t^j$: innovation intensity.
- $s_{lt}^j$: government subsidy.
Innovations are *directed* across technologies,

yet *undirected* within technologies.

A successful innovation

- adds a new product line to the firm’s portfolio, and
- leads to one of two types of innovation:
  1. *incremental* with probability $1 - \alpha$
  2. *breakthrough* with probability $\alpha$.

incremental innovation improves quality by $\lambda > 1$.

breakthrough makes the firm leapfrog the frontier technology.
Innovation, the Quality Ladder and Dynamics

quality level

0 1

product line

j

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Incremental Innovation

quality level

product line

j

$q$

0

1
Radical Innovation

quality level

product line

$0 \leq q \leq 1$
Free Entry

- Endogenously determined mass of entrants $E^j_t$ invests in R&D by paying fixed cost $F_E$ and the variable cost $\left(X^j_{Et}\right)^{\frac{1}{\eta}} \theta^{-\frac{1}{\eta}}$ in terms of skilled labor and enter at the rate $X^j_{Et}$. 
Dirty production $y_{it}^d$ emits $\kappa$ units of carbon per intermediate output:

$$K_t = \int_0^1 \kappa y_{it}^d di,$$

$K_t$: total amount of carbon emission at time $t$
The atmospheric carbon concentration $S_t$ is (Golosov et al., 2011)

$$S_t = \int_0^{t-T} (1 - d_l) K_{t-l}dl,$$

where the amount of carbon emitted $l$ years ago still left in the atmosphere is:

$$d_l = (1 - \varphi_P) \left[ 1 - \varphi_0 e^{-\varphi l} \right]$$

- $\varphi_P \in (0, 1)$: share of permanent emission
- $(1 - \varphi_P) \varphi_0$: transitory component that remains in the first period
- $\varphi \in (0, 1)$: the rate of decay of carbon concentration over time.
Equilibrium Profits (I)

- Unit elastic demand. Thus the profits are

\[
\begin{align*}
\pi_{it}^c &= \tilde{Y}_t \frac{\lambda - 1}{\lambda} & \pi_{it}^d &= 0 & \text{if} & \quad m_{it} > n_{it} \\
\pi_{it}^c &= 0 & \pi_{it}^d &= \tilde{Y}_t \frac{\lambda - 1}{\lambda} & \text{if} & \quad m_{it} < n_{it} \\
\pi_{it}^c &= 0 & \pi_{it}^d &= 0 & \text{if} & \quad m_{it} = n_{it}
\end{align*}
\]

where \( \tilde{Y}_t \equiv Y_t \exp(\gamma (S_t - \bar{S})) \) is net aggregate output.
Not every successful innovation leads to profitable production for two reasons:

1. innovation occurs in technology \( j \) which is behind technology \(- j\),
2. potential zero markup if the tax-adjusted labor productivities are the same with the two technologies.

Probabilities of positive return to a successful innovation:

\[
\Gamma^c_t \equiv \sum_{n \leq m} \mu_{nt} + \alpha \left(1 - \sum_{n \leq m} \mu_{nt}\right) \mathbb{I}(m \geq 0)
\]
\[
\Gamma^d_t \equiv \sum_{n \geq m} \mu_{nt} + \alpha \left(1 - \sum_{n \geq m} \mu_{nt}\right) \mathbb{I}(m \leq 0)
\]
For expositional clarity, assume that firms maximize instantaneous profits (i.e., “myopic”).

Full model will relax this assumption.

Define the expected value of a successful innovation as

$$\bar{v}_t^j = \Gamma_t^j \Pi_{it}^j$$

Thus equilibrium incumbent innovation decision for $j \in \{c, d\}$:

$$\max_{X_t^j \geq 0} \left\{ X_t^j \bar{v}_t^j - \left(1 - s_{lt}^j\right) w_t^s \left[ \left(X_t^j\right)^{1/\eta} \theta^{-1/\eta} \left(u_t^j\right)^{\eta-1/\eta} + \mathbb{I}(X_t^j > 0) u_t^j F_t \right] \right\}$$
Equilibrium Innovation Decision (II)

- Conditional on investing in R&D, the equilibrium innovation rate is

\[ x_{lt}^j = \left( \frac{\bar{v}_t^j \eta \theta \frac{1}{\eta}}{1 - s_{lt}^j} w_t^s \right)^{\frac{\eta}{1-\eta}} = \left( \frac{\Gamma_t^j \lambda - 1}{\lambda} \tilde{Y}_t \eta \theta \frac{1}{\eta} w_t^s \left( 1 - s_{lt}^j \right) \right)^{\frac{\eta}{1-\eta}}. \]

Similar for entrant innovation. Increasing in:
- Higher net output \( (\tilde{Y}_t) \),
- higher markups \( (\lambda) \)
- lower scientists wages \( (w_t^s) \)
- policy: subsidies to research increase clean innovation \( (s_{lt}^c) \).

Through the \( \Gamma_t^j \)'s,

1. carbon taxes \( (\tau^d) \) increase clean innovation (reduce dirty innovation).
2. innovation is path-dependent:
   - large technology gaps \( \rightarrow \sum_{n \leq m} \mu_{nt} \) very small \( \rightarrow \Gamma_t^c \) very small \( \rightarrow \) discouraging clean innovation

Hence clean innovation will naturally self-reinforce over time.
Full model with forward-looking R&D decisions

- Generalizes to forward-looking firms.
- Value function of a firm with a vector of tech gaps $\vec{n}^j \equiv [n^j_1, ..., n^j_{u^j_t}]$:

$$
\begin{align*}
  rV_{\vec{n}^j, t} - \dot{V}_{\vec{n}^j, t} &= \\
  \left\{ \begin{array}{l}
    \pi^j_{n_i, t} + z_t^j \left( V^j_{\vec{n}^j_{-i}, t} - V^j_{\vec{n}^j, t} \right) \\
      \quad + z_t^{-j} (1 - \alpha) \left( V^j_{\vec{n}^j_{-i}, t} \cup \{ n^j_i - 1 \}, t - V^j_{\vec{n}^j, t} \right) \\
      \quad + z_t^{-j} \alpha \left( V^j_{\vec{n}^j_{-i}, t} - V^j_{\vec{n}^j, t} \right) \\
      \quad + \sum_{i=1}^{u^j} z_t^{j-1} \left( 1 - \alpha \right) \left( V^j_{\vec{n}^j_{-i}, t} \cup \{ n^j_i - 1 \}, t - V^j_{\vec{n}^j, t} \right) \\
    + \int \max_{x_{t+1} \geq 0} \left[ u^j_t x_t \left( V^j_{\vec{n}^j \cup \{ n^j_{u+1} \}, t} - V^j_{\vec{n}^j, t} \right) \right] \\
    \left[ (1 - s^j_{l, t}) u^j_t w^s_t \left( (x_t^j)^{\frac{1}{\eta}} \theta^{-\frac{1}{\eta}} + \mathbb{I}(x^d_{n, t} > 0) F_{l, t} \right) \right] dF_{l, t}.
  \end{array} \right.
\end{align*}
$$
Empirical Strategy

The model has 14 parameters/variables to be determined:

\[
\{\rho, \bar{S}, \gamma, \varphi, \varphi_0, \varphi_P, \kappa, L^s, \alpha, \eta, \theta, \lambda, F_I, F_E\} \quad \text{and} \quad \{\mu_{n_0}\}_{n=-\infty}^{\infty}
\]

Proceed in four steps:

1. external calibration: \(\rho, \bar{S}, \gamma, \varphi, \varphi_0, \varphi_P, \kappa\)
2. direct estimation from micro data: \(L^s, \alpha, \eta\).
3. match patent data to generate initial distribution: \(\mu_n\)
4. simulated method of moments: \(\theta, \lambda, F_I, F_E\)
Data & Sample (I)

Data:
- Longitudinal Business Database and Economic Censuses,
- National Science Foundation’s Survey of Industrial R&D,
- NBER Patent Database.

Sample:
- Innovators in the US Energy Sector
- Build unbalanced panel with six periods: 1975-1979, . . . , 2000-2004
- Firms must be innovative in first period observed
- Collect operating data, R&D expenditures, and innovations by period
Data & Sample (II)

- Energy sector
  - start with the patent data,
  - classify patents into energy-related patents,
  - classify patents as dirty vs clean using 150,000 USPCs,
  - match patents to firms using name-location matching algorithm,
  - classify firms as dirty vs clean using their patent portfolio,
  - using 400 SIC3, construct dirty and clean patent stock.
Sample properties

- 6228 observations from 1576 firms
- 19% of all U.S. R&D industrial expenditures
- 70% of industrial patents for the energy sector
## Parameters

<table>
<thead>
<tr>
<th>Par.</th>
<th>Value</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>1% and 0.1%</td>
<td>Nordhaus and Stern</td>
</tr>
<tr>
<td>$\bar{S}$</td>
<td>581 GtC</td>
<td>Preindustrial carbon stock</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>$5.3 \times 10^{-5}$ GtC$^{-1}$</td>
<td>$4^\circ$C increase about 4-5% GDP drop</td>
</tr>
<tr>
<td>$\phi_P$</td>
<td>20%</td>
<td>Permanent emission IPCC (2007)</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>0.006636</td>
<td>carbon’s half life of 30 years</td>
</tr>
<tr>
<td>$\varphi_0$</td>
<td>0.4576</td>
<td>Evolution of carbon stock 1900-2000</td>
</tr>
<tr>
<td>$L^s$</td>
<td>5.5%</td>
<td>S&amp;E workers in energy sector</td>
</tr>
<tr>
<td>$\eta$</td>
<td>45%</td>
<td>Reg R&amp;D$ and Scientist count on SIC#</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>4%</td>
<td>prob of major entry patent (&gt;$90$ percentile)</td>
</tr>
<tr>
<td>$\mu_n$</td>
<td>see figure</td>
<td>patent stock count by SICs</td>
</tr>
</tbody>
</table>
Carbon Cycle Match

We use the following to match the carbon concentration:

\[ S_t = \int_0^{t-1900} (1 - d_l) K_{t-1} dl + S_{1900}, \quad t \in [1900, 2008]. \]

where

\[ d_l = (1 - \varphi) \left( 1 - \varphi_0 e^{-\varphi l} \right) . \]
Clean lead in 6%, and dirty lead in 60% of product lines, but in some cases by quite a lot.
Simulated Method of Moments Estimates

- Four parameters estimated from four moments (three from microdata and one aggregate):

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>Innovation productivity</td>
<td>0.500</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Innovation step size</td>
<td>1.075</td>
</tr>
<tr>
<td>$F_I$</td>
<td>Fixed cost of incumbent R&amp;D</td>
<td>0.002</td>
</tr>
<tr>
<td>$F_E$</td>
<td>Fixed cost of entry</td>
<td>0.035</td>
</tr>
</tbody>
</table>
Moments in the Data and Model

<table>
<thead>
<tr>
<th>Moments</th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry Share</td>
<td>0.013</td>
<td>0.013</td>
</tr>
<tr>
<td>Exit Rate</td>
<td>0.018</td>
<td>0.018</td>
</tr>
<tr>
<td>Average R&amp;D/Sales</td>
<td>0.066</td>
<td>0.066</td>
</tr>
<tr>
<td>Aggregate Sales/Worker Growth</td>
<td>0.007</td>
<td>0.012</td>
</tr>
</tbody>
</table>
Non-targeted Moments

## Comparison of Growth Distribution

<table>
<thead>
<tr>
<th>Change over 5-Years:</th>
<th>Employment Growth Probability</th>
<th>Notes: Table compares non-targeted moments in model and data.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decrease 75% or more</td>
<td>0.17</td>
<td></td>
</tr>
<tr>
<td>Decrease 50% or more</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td>Decrease 25% or more</td>
<td>0.27</td>
<td></td>
</tr>
<tr>
<td>Increase 25% or more</td>
<td>0.24</td>
<td></td>
</tr>
<tr>
<td>Increase 50% or more</td>
<td>0.17</td>
<td></td>
</tr>
<tr>
<td>Increase 75% or more</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td>Increase 100% or more</td>
<td>0.08</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decrease 75% or more</td>
<td>0.17</td>
<td>0.11</td>
</tr>
<tr>
<td>Decrease 50% or more</td>
<td>0.20</td>
<td>0.15</td>
</tr>
<tr>
<td>Decrease 25% or more</td>
<td>0.27</td>
<td>0.25</td>
</tr>
<tr>
<td>Increase 25% or more</td>
<td>0.24</td>
<td>0.31</td>
</tr>
<tr>
<td>Increase 50% or more</td>
<td>0.17</td>
<td>0.20</td>
</tr>
<tr>
<td>Increase 75% or more</td>
<td>0.15</td>
<td>0.14</td>
</tr>
<tr>
<td>Increase 100% or more</td>
<td>0.08</td>
<td>0.11</td>
</tr>
</tbody>
</table>
Climate Dynamics in the Laissez-faire Economy (I)

Innovation Rates

- Clean Innovation
- Dirty Innovation

Number of Years

Climate Change and Technology
October 3, 2013.
Climate Dynamics in the Laissez-faire Economy (II)

Formula to compute the temperature changes:

$$\Delta temperature = \frac{\lambda (\ln S_t - \ln \tilde{S})}{\ln 2}.$$
Optimal Policy (I)

- We consider two policies
  - Carbon tax: $\tau_t$
    - multiples of the innovation step size $\lambda \quad \Longrightarrow \quad 1 + \tau_t = \lambda^m_t$.
  - Clean R&D subsidy: $s_t^c$.
    - It is a continuous variable $s_t^c \in [0,1]$.
    - Same subsidy rate for both entrants ($s_{Et}^c$) and incumbents ($s_{It}^c$).

- We use two baseline discount rates for social planner.
  - $\rho = 1\%$: similar to Nordhaus (1994, 2008).
  - $\rho = 0.1\%$: similar to Stern (2007)

- private discount rate is always 1%.
Optimal Policy (II)

We consider two alternatives

1. **Constant policy:** \( \tau_t^d = \tau^d \) and \( s_t^c = s^c \).

2. **Time-varying policy:** 3 time cutoffs and 4 policy levels:

\[
\tau_t^d = \begin{cases} 
\tau_1^d & \text{for } t \in [0, t_1^\tau) \\
\tau_2^d & \text{for } t \in [t_1^\tau, t_2^\tau) \\
\tau_3^d & \text{for } t \in [t_2^\tau, t_3^\tau) \\
\tau_4^d & \text{for } t \in [t_3^\tau, \infty)
\end{cases}
\]

\[
\left( \tau_t^d, s_t^c \right) = \begin{cases} 
s_1^c & \text{for } t \in [0, t_1^s) \\
s_2^c & \text{for } t \in [t_1^s, t_2^s) \\
s_3^c & \text{for } t \in [t_2^s, t_3^s) \\
s_4^c & \text{for } t \in [t_3^s, \infty)
\end{cases}
\]

Daron Acemoglu (MIT)  
Climate Change and Technology  
October 3, 2013. 68 / 82
Optimal Constant Policy (I)

**Optimal Constant Policy**

<table>
<thead>
<tr>
<th>$\rho_{sp} = 1%$</th>
<th>$\rho_{sp} = 0.1%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau$</td>
<td>$s$</td>
</tr>
<tr>
<td>16%</td>
<td>61%</td>
</tr>
<tr>
<td>44%</td>
<td>95%</td>
</tr>
</tbody>
</table>
Optimal Constant Policy (II)

Innovation Rates

Number of Years

Innovation Rates

$x_c: \rho_{sp} = 1\%$

$x_c: \rho_{sp} = 0.1\%$

$x_d: \rho_{sp} = 1\%$

$x_d: \rho_{sp} = 0.1\%$
Optimal Constant Policy (III)

Temperature (Constant World)

- \( \rho_{sp} = 1\% \)
- \( \rho_{sp} = 0.1\% \)

Temperature (Adjusting World)

- \( \rho_{sp} = 1\% \)
- \( \rho_{sp} = 0.1\% \)
Optimal Time-Varying Policy (I)

Optimal Policies, $\rho_{sp} = 1\%$

Optimal Policies, $\rho_{sp} = 0.1\%$
**Welfare costs of Cons Pol relative to TV**

<table>
<thead>
<tr>
<th>$\rho_{sp} = 1%$</th>
<th>$\rho_{sp} = 0.1%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>16%</td>
<td>0.3%</td>
</tr>
</tbody>
</table>
Counterfactual Policy Analysis (I)

3 counterfactual exercises:

1. **Carbon tax only**: policymaker uses only time-varying carbon tax.
2. **50 year delay**: policymaker plans to take action starting in 50 years with both time-varying policies.
3. **Business as usual**: we keep the current policies in place forever.
Counterfactual Policy Analysis (II)

Optimal Policies, $\rho_{sp} = 1\%$

Optimal Policies, $\rho_{sp} = 0.1\%$
### Welfare Costs

<table>
<thead>
<tr>
<th></th>
<th>Carbon Tax Only</th>
<th>50-year Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{sp} = 1%$</td>
<td>4.2%</td>
<td>8.0%</td>
</tr>
<tr>
<td>$\rho_{sp} = 0.1%$</td>
<td>3.4%</td>
<td>16.6%</td>
</tr>
</tbody>
</table>

- Avoiding R&D subsidy has a significant welfare cost.
- Delaying policy intervention is even worse, particularly for low discount rate.
Estimate of current subsidy:

- In our sample period of 30 years, 49% of clean R&D and 11% of dirty R&D is federally funded. We take the current subsidy as

\[ 1 - s = \frac{1 - 49\%}{1 - 11\%} \implies s = 43\%. \]

Estimate of current carbon tax:

- Policy makers estimate the social cost of carbon as $143 per ton of carbon dioxide.
- Total emission is around 1.58 billion tons of carbon dioxide.
- Total sales around $1 trillion.
- Hence the estimated tax is

\[ \tau = \frac{143 \times 1.58 \times 10^9}{10^{12}} \approx 24\%. \]
**Welfare Costs**

<table>
<thead>
<tr>
<th></th>
<th>$\tau = 24%$, $s = 43%$</th>
<th>$\tau = 0$, $s = 43%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{sp} = 1%$</td>
<td>18%</td>
<td>100%</td>
</tr>
<tr>
<td>$\rho_{sp} = 0.1%$</td>
<td>8%</td>
<td>100%</td>
</tr>
</tbody>
</table>

- Too much carbon tax and too little R&D subsidy compared to optimal constant policy: $\tau^d = 16\%$ and $s^c = 61\%$. 
Optimal policy in the presence of endogenous and directed technological change may rely heavily on R&D subsidy as well as carbon tax.

Intuition:
- carbon tax generates static distortion: Leads to reallocation into less productive technology \(\implies\) Loss of current consumption
- R&D subsidy generates dynamic distortion: innovate without any growth for a while until clean takes over.

Current policy estimates are overtaxing carbon and undersubsidizing R&D.

Avoiding R&D subsidy has sizable welfare costs (3.4%-4.2%)

Delaying policy intervention by 50 years has very large welfare costs (8%-16.6%)
US emission is around 15% of the world emission.

Foreign emission has no effect on policy rankings:

\[ S_t = S_t^{Domestic} + S_t^{Foreign} \]

\[ Y_t = e^{-\gamma(S_t^{Domestic} + S_t^{Foreign} - \bar{S})} \exp \left( \int_0^1 \ln y_{it} \, di \right) \]

\[ U_t = \ln C_t = -\gamma S_t^{Foreign} - \gamma \left( S_t^{Domestic} - \bar{S} \right) + \int_0^1 \ln y_{it} \, di \]
Are These Conclusions too Optimistic?

Perhaps. Only more empirical work can tell.

But things to watch out for:

- Research subsidies may be ineffective → then more reliance on carbon tax
- Research might be much lower → then more reliance on carbon tax
- There is in practice a lot of uncertainty associated with new technologies → then more reliance on carbon tax
- There may be less room for “building on the shoulders of giants’” in green technologies → then more reliance on carbon tax
- Elasticity of substitution may be lower → then more reliance on carbon tax
If Technology Is so Powerful, Can We Afford Delay?

IT'S SETTLED...
WE AGREE TO SIGN
A PLEDGE TO HOLD
ANOTHER MEETING
TO CONSIDER CHANGING
COURSE AT A DATE
YET TO BE DETERMINED.

CLIMATE CHANGE

WORLD LEADERS