Forecasting Technological Innovation

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Abstract:

Using a database of sixty-two different technologies, we study the issue of forecasting technological progress. We do so using the following methodology: pretending to be at a given time in the past, we forecast technology prices for years up to present day. Since our forecasts are in the past, we refer to it as *hindcasting* and analyze the predictions relative to what happened historically. We use hindcasting to evaluate a variety of different hypotheses for technological improvement. Our results indicate that forecasts using production are better than those using time. This conclusion is robust when analyzing randomly chosen subsets of our technology database. We then turn to investigating the interdependence of revenue and technological progress. We derive analytically an upper bound to the rate of technology improvement given the condition of increasing revenue and show empirically that all technologies fall within our derived bound. Our results suggest the observed advantage of using production models for forecasting is due in part to the direct relationship between production and revenue.

Keywords: experience curve, learning curve, performance curve, technology evolution, innovation

1 Introduction and background

Technology forecasting is a pervasive tool in the fields of engineering, economics, management science, and public policy. Arguably, the most consequential applications rest at the intersection of these disciplines. Different strategies for forecasting technological progress have been proposed [Moo65, Wri36, KM06, KM08, God82, SSC00, Nor09]. Simple models that track a performance metric as a function of one or two explanatory variables are widespread. In this work, we use the term *performance curve* to describe such simple models, which we define very generally to be a model of some performance metric (here, unit price) as a function of some proxy for experience (such as time or production). Perhaps the most famous performance curve model is Moore's law [Moo65], which states that the technology improves exponentially with time. Moore proposed exponential improvement originally for the density of transistors on a chip but later found that the relationship held for many different metrics for progress, including unit price. Another widely used performance curve model today is a power law relationship between the unit price of a technology p and its cumulative production q. Specifically, $p \propto q^{-w}$, where the exponent w is the rate of improvement. This model is referred to as "learning-by-doing" or Wright's law after his seminal 1936 study on aircraft costs [Wri36]. A similar power law relationship betwen unit price and *annual* production was proposed by Goddard [God82]. Alternative hypotheses utilizing time [KM06, KM08] and combinations of time, annual production, and cumulative production [SSC00, Nor09] also exist in the literature.

Performance curves aggregate all sources of price change, including but not limited to changes in input prices, economies of scale, labor learning, product and process innovation, and standardization. Furthermore, technological progress is collapsed into a single performance metric, ignoring all other potential metrics of improvement. In spite of these simplifications, performance curves have been shown empirically to be plausible models for describing technologies from industries as diverse as chemicals, agriculture, energy, and information technology.

Despite the broad use of performance curves, no systematic study comparing competing hypotheses across an ensemble of technologies has been published to our knowledge. In this work, we do exactly that. We use hindcasting methodology to assess model performance. The significance of our results is assessed by analyzing randomly chosen subsets of technologies to determine whether the same conclusions hold. We broaden the analysis to study revenue dynamics and its interdependence with technological progress. We present an analytical framework for investigating revenue and compare predictions to empirical observations. Insight into revenue as a driver for technology evolution is discussed in the context of the results comparing competing hypotheses for performance curves.

2 Models

We analyze a suite of different hypotheses for technological progress, shown in Eq.'s 1-6. The first three – Moore's law [Moo65], Goddard's law [God82], and Wright's law [Wri36]

– are hypotheses proposed in the literature. They are all regression models with fitted intercepts, denoted here by b. The remaining models – Moore's law random walk, Goddard's law random walk, and Moore-Goddard's law random walk – are time series models that have not been proposed in the literature, to our knowledge. We refer to them as *random walk* models because unit technology price typically contains drift and noise; however, we do not write the noise term explicitly in Eq.'s 4-6. For brevity, the models will be referred to by the abbrieviation following their names from here onward (e.g. ML, GL, etc.). The variables p_t, x_t, and q_t are the unit price, annual production, and cumulative production in year t, respectively. The parameters m, g, w, $\bar{m}$, $\bar{g}$, $\bar{f}_1$, $\bar{f}_2$, and b are fitted using ordinary least squares using n consecutive years of data as the sample set. A bar above a parameter indicates it is for a time series, as opposed to regression, model.

Moore's law (ML)

$$\log p_t = b - mt \tag{1}$$

Goddard's law (GL)

$$\log p_t = b - g \log x_t \tag{2}$$

Wright's law (WL)

$$\log p_t = b - w \log q_t \tag{3}$$

Moore's law random walk (MRW)

$$\log p_{t+1} = \log p_t - \bar{m} \tag{4}$$

Goddard's law random walk (GRW)

$$\log p_{t+1} = \log p_t - \bar{g} \log \left(\frac{x_{t+1}}{x_t} \right) \tag{5}$$

Moore-Goddard's law random walk (MGRW)

$$\log p_{t+1} = \log p_t - \bar{f}_1 \log \left(\frac{x_{t+1}}{x_t} \right) - \bar{f}_2 \tag{6}$$

3 Methodology

The first part of this work is systematically analyzing the performance of the models across an ensemble of different technologies. We use sixty-two technologies from the Performance Curve Database [PCD], an online database of performance curves, as our test bed. Only data sets with at least ten consecutive years of annual price and production data were used. Four IT technologies are incorporated into the analysis: hard disk drives, transistors, laser diodes, and DRAM. Acrylic fiber, titanium sponge, geothermal electricity, monochrome television, and beer are a few of the non-IT technologies. A complete list of technologies with references to their original sources and a selection of fit model parameters are in Section 8.1. All data sets are from studies with a scope at least as broad as a national industry (e.g. wind turbine prices in Denmark), while many are global average prices.

To evaluate performance of the models, we use hindcasting methodology. For a given data set, we select a specified number of data points in the series to use as the sample set. The sample set size n ranges from five to fifteen. Results are presented for n=6 unless otherwise noted. We use the sample set to fit the parameters of the model in question. Using the resultant parameter fits, we make a forecast of the unit price for each year through the end of the data series. Since our forecasts are actually in the past, we refer to it as *hindcasting* and compare our predictions to what happened in reality. To quantify forecast accuracy, we use the logarithmic hindcasting error

$$\epsilon = \log p - \log \hat{p}, \tag{7}$$

where $\hat{p}$ is the forecast and p is the historical unit price. The sample set is then shifted one year toward the future, the parameters refit, and a new forecast is made for each year through the last year of available data. The process continues until the sample set comprises the final n data points in the time series. We refer to the last data point in the sample set as the *origin*. The *horizon* is the number of years in the future relative to the origin of the forecast. For a given n, the error ϵ is therefore calculated for each combination of technology, model, origin, and horizon, where each combination thereof is referred to as an *event*.

To assess model performance across the ensemble of technologies, we first normalize the errors of each technology by the standard deviation (k) of the residuals fit to a Gaussian distribution with zero mean. The standard deviation is calculated using the entire data series of each technology. We take the residuals from the fit to MRW and note that all results discussed here hold irrespective of which model is used for normalization. Then, we take an event average of the absolute values of the errors as a function of horizon. Statistical significance is addressed in Section 4.

Implicit in this approach is the assumption that the underlying process of evolution is equivalent for every technology. Said in another way, the models that perform best do so irrespective of the specific technology or industry. Results analyzing subsets of data divided by industry – as labeled in the appendix – support that this is a valid assumption; however, we note that this hypothesis is the subject of ongoing re-evaluation as more data becomes available for analysis.

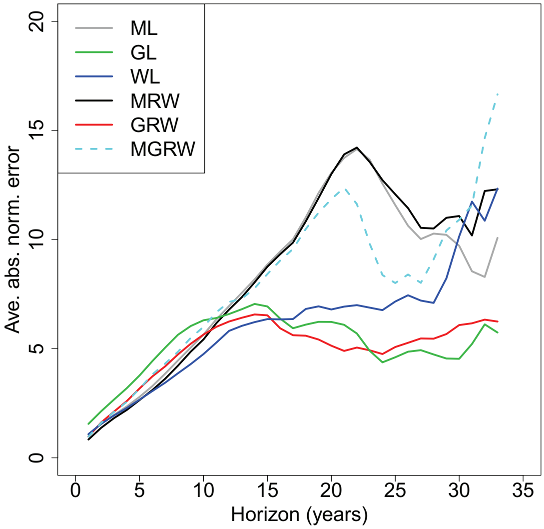

Figure 1: Absolute value of the normalized hindcast error averaged over the ensemble of technologies vs. horizon, for each model: Moore's law (ML), Goddard's law (GL), Wright's law (WL), Moore's law random walk (MRW), Goddard's law random walk (GRW), and Moore-Goddard's law random walk (MGRW).

4 Comparing competing hypotheses

Fig. 1 shows the normalized absolute value of the hindcast error averaged across all technologies for each model as a function of horizon. First, we note that the additional level of complexity brought about by using a multivariate model (MGRW) does not lead to more accurate forecasts. The same conclusion holds for other multivariate models we investigated, including those not presented in this work. All subsequent results will exclude multivariate models unless otherwise noted.

Let us now focus on the univariate models, shown as solid curves in Fig. 1. For horizons greater than approximately ten to fifteen years, the models bifurcate. Two models perform noticeably poorly: ML and MRW. These are the two models that use time as an explanatory variable. Forecasts based on some form of production (annual, cumulative, etc.) make better forecasts than those based on time. For horizons shorter than ten years, the models perform roughly equivalently, with the exception of GL, which performs notably poorer. This result is consistent with recent work by Bela *et al.* [NFBT11].

We observe a difference in relative forecasting accuracy of the performance curve models formulated in terms of production versus time; however, is the difference statistically significant? We note that multiple factors influence the increasingly erratic behavior ob-

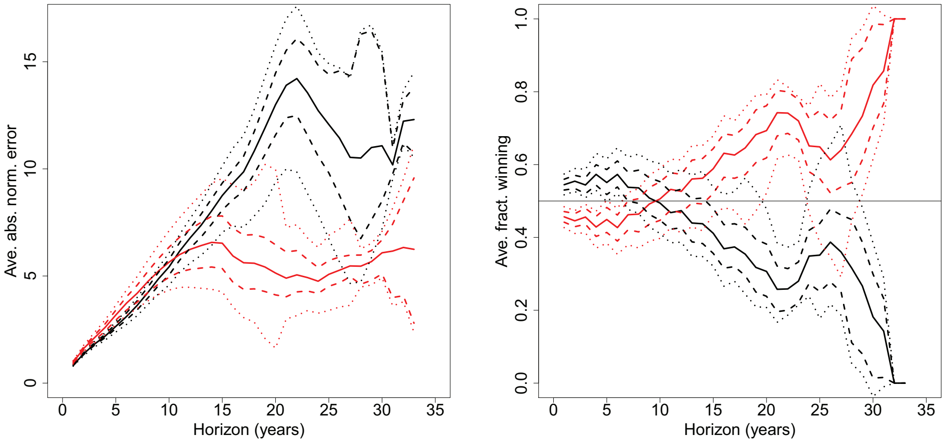

Figure 2: Left: Average of the absolute value of the normalized error for MRW (black) and GRW (red) as a function of horizon. Right: Average of the events won by MRW (black) and GRW (red) as a function of horizon. For both plots, the solid curve is an average over all sixty-two data sets; the dashed (dotted) curve is the average +/- the standard deviation across one hundred randomly chosen subsets of size forty (twenty).

served at increasing horizons. First, as one might intuitively expect, the forecasting error increases as a function of horizon, as does the spread of the distribution of forecasting errors for an ensemble of datasets. Second, as the horizon increases, a decreasing number of technologies are contributing to the average (average data set length is 18 years). These factors have the effect of rendering any observed differences between model performance less significant with increasing horizon. Said in another way, an error bar placed around each curve in Fig.1 would increase in magnitude with horizon. This motivates calculations assessing the statistical significance of our results.

To approach addressing this question, we perform the following robustness analysis. Of the sixty-two technology ensemble, we randomly select m data sets to form a subset. From the subset, we calculate two quantities for MRW and GRW: 1) the average of the absolute value of the normalized error as a function of horizon and 2) the fraction of events for which MRW has the lowest error compared to GRW and vice versa as a function of horizon (which add to unity at every horizon). We chose MRW and GRW specifically as representative of models formulated in terms of time and production. After analyzing one subset, we randomly select another subset and then repeat the analysis. The process is repeated for 100 randomly selected subsets. We take the average and the standard deviation of the two quantities as a function of horizon for each subset size m.

Results are plotted in Fig. 2 for $m = 40$ and 20. The left graph shows the average of the absolute value of the normalized error for MRW (black) and GRW (red) as a function of horizon. On the right, we plot the average of the events won by MRW (black) or GRW (red) as a function of horizon. For both plots, the solid curve is an average over all sixty-two data sets; the dashed (dotted) curve is the average +/- the standard deviation across the randomly chosen subsets of size forty (twenty). When the subset size decreases from forty to twenty, there is greater variability in the resultant average curves, which is to be expected. However, even with a subset size of twenty, the confidence intervals overlap mildly at horizons greater than fifteen years.

We close this section by noting that assessing the statistical significance of our results is a subject of ongoing investigation. Both more and longer data sets would permit a more conclusive statement about the relative advantage of production over time in forecasting technological innovation. We continue to work toward expanding the Performance Curve Database with other technologies to continue to test this hypothesis. Additionally, we hope the Performance Curve Database will facilitate and promote research by other parties in the general area of technology evolution.

5 Relationship to revenue

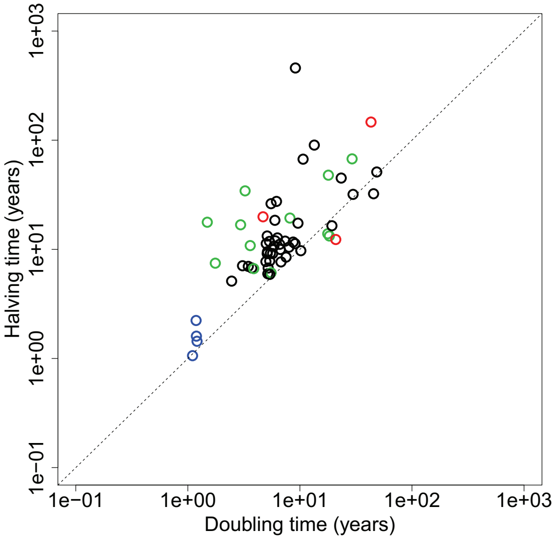

Figure 3: Halving time of unit price vs. doubling time of annual production. The color of the symbol reflects the industry of the technology: chemical (black), energy (green), IT (blue), and other (red). Please note that three data sets were excluded because of negative annual production growth (electric range, free standing gas range, and onshore gas pipeline).

In the previous section, our results indicate that production is a better indicator of price dynamics. To gain further insight into drivers of technological process, we propose one additional model, which we call the “Revenue random walk”.

Revenue random walk (RRW)

$$\log p_{t+1} = \log p_t - \bar{r} \log \left(\frac{x_{t+1} p_{t+1}}{x_t p_t} \right) \tag{8}$$

The product of the annual production (x_t) and unit price (p_t) is the annual revenue, which is the explanatory variable for this model. Eq. 8 is similar in form to Goddard’s law random walk, with revenue in place of simply annual production. In fact, after rearrangement, one can show that Eq. 8 is equivalent to Goddard’s law random walk, where $\bar{g} = \bar{r}/\left(1 - \bar{r}\right)$[1]. Therefore, one of the best performing models is effectively tracking revenue dynamics, given the direct relationship between revenue and production.

We can further probe the relationship between revenue and price dynamics by formulating the problem in the following manner. First, let us express the revenue as

$$r_t = x_t p_t. \tag{9}$$

We now drop the subscript $_t$ for brevity. The change in revenue is then

$$\frac{dr}{dt} = \frac{dp}{dt} x + p \frac{dx}{dt}. \tag{10}$$

Please note that this derivation is formulated in terms of continuous time dynamics. In order for the industry’s revenue to grow or stay constant, we have the condition that

$$\frac{dr}{dt} = \frac{dp}{dt} x + p \frac{dx}{dt} \geq 0. \tag{11}$$

One notable set of solutions to Eq. 11 is

$$\begin{aligned} p &= k_p e^{-t/\tau_p} \\ x &= k_x e^{t/\tau_x}. \end{aligned} \tag{12}$$

Exponential decay of the unit price is simply ML (Eq. 1, which we know to be a plausible model, albeit not the most accurate). Furthermore, empirically we observe that production does grow roughly exponentially across all technologies investigated here [NFBT11]. Our solution set is therefore consistent with empirical observations.

Eq. 12 leads to the condition

$$\frac{\tau_p}{\tau_x} \geq 1. \tag{13}$$

When the firm’s revenue is constant, and the price and production are exponential solutions, the timescale of exponential decay of the price must be greater than the timescale of exponential growth of the production for the revenue to increase.

[1] Similarly, a regression model in terms of annual revenue can easily be shown to be equivalent to Goddard’s law.

Let us define the halving time as the amount of time (in years) it takes for the unit price to half. We define the doubling time as the amount of time it takes annual production to double. We calculate the halving and doubling times for every technology and construct the scatter plot in Fig. 3. In order for the revenue to remain constant or increase, the rate of production scale-up must be equal to or greater than the rate of price reduction. In other words, we expect the doubling time to be less than or equal to the halving time. Indeed, as seen in Fig. 3, the vast majority of the technologies lie above the identity line. This means that Eq. 13 is met; the overall industry revenue for nearly all technologies is increasing.

This derivation is somewhat unsatisfying because of the imposed functional form for the production. Let us consider another solution set to Eq. 11, and, in doing so, derive an upper limit for the exponent for GRW. We consider $p = k_p x^{-g}$. Using the condition of increasing or flat revenue, Eq. 11, we arrive at the condition $g \leq 1$. Therefore, the scaling exponent g must be less than or equal to unity, the bound for maintaining constant revenue. Empirically, there are no technologies in our analysis where g is greater than unity (outside the error of the fit). The only ones that approaches this value are the Hard Disk Drive, Pentaerythritol, and Phthalic Anhydride data sets, for which $g = 1.0$ (see Section 8.1 for values of g for other technologies). This section provides empirical support for the importance of revenue as a key driver for technological evolution.

6 Discussion

In this work, we comprehensively evaluated competing hypotheses for technology improvement. Using a database of sixty-two different technologies as a test bed, we applied hindcasting methodology to assess the relative performance of the models across the ensemble of data sets. Our results indicate that at long time horizons, production is a better indicator of price dynamics compared to time. This conclusion was robust from analyzing samples of randomly chosen subsets of twenty and forty technologies. However, we note this result is the subject of ongoing investigation.

We then considered revenue as a driver for technological progress. We show that for nearly all technologies, the halving time of the price is less than the doubling time of the annual production, the condition required for increasing industry revenue. We formulate our observations in terms of a simple analytical framework and derive an upper bound for the rate of technological progress in terms of annual production given the condition of increasing revenue. The derived bound is consistent with empirical results from our test bed, where categorically every technology is within this limit. Our results support that revenue is a key driver for technological evolution.

The use of production for forecasting technological progress via a learning or experience curve is often justified in the literature by Arrow's explanation [Arr62]: production is a proxy for accumulated experience, and *learning-by-doing* provides the opportunities for innovation and cost reductions (for further discussion, see [DT84, LE90, MS01, Nem06]). However, our results investigating revenue dynamics suggest that the success of the production models is likely due in part to the direct relationship between production and revenue. Revenue may better account for industry-wide decision-making that affects technology price dynamics. This is a new angle to the typically posited explanation for using production. Furthermore, our results emphasize the importance of analyzing technology evolution in the context of a broader economic framework.

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8 Appendix

8.1 Data sets

All data sets can be found on the Performance Curve Database [PCD]. In the tables below, we list the sixty-two data sets used in the above analysis and their original sources. The technologies are divided into separate tables by industry, labelled in the table caption. We also include a selection of parameter fits, including Moore's law (m), Goddard's law (g), Wright's law (w), the halving time of unit price (τ_h), and the doubling time of annual production (τ_d).

Table 1: Industry: energy.

Technology	m	g	w	τ_h	τ_d
CCGT Electricity [CC02]	0.020	0.10	0.12	34	3.2
Crude Oil [Gro72]	0.010	0.38	0.17	68	29
Electric Power [Gro72]	0.036	0.42	0.34	19	8.1
Ethanol [GCNL04]	0.052	0.89	0.36	13	18
Geothermal Electricity [SE09]	0.050	0.81	0.50	14	18
Motor Gasoline [Gro72]	0.014	0.32	0.21	48	18
Offshore Gas Pipeline [Zha99]	0.11	0.21	0.49	6.1	5.5
Onshore Gas Pipeline [Zha99]	0.015	0.13	0.11	45	-
Photovoltaics [May05]	0.064	0.34	0.30	11	3.6
Photovoltaics 2 [Nem06]	0.10	0.56	0.49	6.7	3.9
Wind Electricity [SE09]	0.093	0.17	0.18	7.5	1.8
Wind Turbine [NAD$^+$03]	0.041	0.14	0.13	17	3.0
Wind Turbine 2 [NAD$^+$03]	0.039	0.085	0.072	18	1.5

Table 2: Industry: other.

Technology	m	g	w	τ_h	τ_d
Beer [Gro72]	0.035	0.23	0.20	20	4.7
Electric Range [Gro72]	0.023	-0.023	0.29	31	-
Free Standing Gas Range [Gro72]	0.020	-0.48	0.56	35	-
Monochrome TV [Gro72]	0.056	0.44	0.28	12	21
Refined Cane Sugar [Gro72]	0.0047	0.14	0.32	150	43

Table 3: Industry: chemical.

Technology	m	g	w	τ_h	τ_d
Acrylic Fiber [Lie84]	0.10	0.70	0.58	6.8	5.2
Acrylonitrile [Lie84]	0.076	0.49	0.43	9.1	5.1
Aluminum [Lie84]	0.010	0.14	0.13	67	11
Ammonia [Lie84]	0.090	0.81	0.83	7.7	6.8
Aniline [Lie84]	0.058	0.48	0.93	12	6.0
Benzene [Gro72]	0.062	0.56	0.74	11	6.6
Bisphenol A [Lie84]	0.061	0.43	0.41	11	5.0
Caprolactum [Lie84]	0.12	0.85	0.54	6.0	5.2
Carbon Disulfide [Lie84]	0.021	0.25	0.47	32	45
Cyclohexane [Lie84]	0.052	0.33	0.37	13	5.1
Ethanolamine [Lie84]	0.062	0.77	0.53	11	9.0
Ethyl Alcohol [Lie84]	0.014	-0.083	0.17	51	49
Ethylene [Gro72]	0.037	0.31	0.18	18	6.0
Ethylene 2 [Lie84]	0.065	0.55	0.49	11	5.9
Ethylene Glycol [Lie84]	0.066	0.72	0.70	10	8.0
Formaldehyde [Lie84]	0.060	0.71	0.63	12	8.7
Hydrofluoric Acid [Lie84]	0.0015	0.035	0.018	460	9.1
LD Polyethylene [Gro72]	0.10	0.50	0.38	6.8	3.7
Magnesium [Lie84]	0.0077	0.12	0.15	90	13
Maleic Anhydride [Lie84]	0.054	0.47	0.43	13	6.3
Methanol [Lie84]	0.058	0.63	0.68	12	7.4
Neoprene Rubber [Lie84]	0.022	0.80	0.28	32	30
Paraxylene [Gro72]	0.10	0.43	0.42	7.0	3.5
Pentaerythritol [Lie84]	0.042	1.0	0.45	17	19
Phenol [Lie84]	0.082	0.87	0.84	8.5	7.5
Phthalic Anhydride [Lie84]	0.071	1.0	0.88	9.7	10
Polyester Fiber [Lie84]	0.13	0.47	0.48	5.1	2.5
Polyethylene HD [Lie84]	0.10	0.40	0.46	7.1	3.1
Polyethylene LD [Lie84]	0.089	0.68	0.50	7.8	5.4
Polystyrene [Gro72]	0.058	0.34	0.24	12	5.3
Polyvinylchloride [Gro72]	0.075	0.57	0.43	9.2	5.5
Primary Aluminum [Gro72]	0.025	0.23	0.25	28	6.2
Primary Magnesium [Gro72]	0.026	0.18	0.17	26	5.5
Sodium [Lie84]	0.015	0.38	0.47	45	23
Sodium Chlorate [Lie84]	0.040	0.51	0.40	17	9.6
Styrene [Lie84]	0.069	0.66	0.59	10	6.7
Titanium Sponge [Gro72]	0.12	0.44	0.37	5.9	5.4
Urea [Lie84]	0.073	0.54	0.49	9.5	5.1
Vinyl Acetate [Lie84]	0.076	0.61	0.60	9.1	5.7
Vinyl Chloride [Lie84]	0.090	0.63	0.64	7.7	5.0

Table 4: Industry: information technology.

Technology	m	g	w	τ_h	τ_d
DRAM [Cul08]	0.43	0.74	0.72	1.6	1.2
Hard Disk Drive [Cou08]	0.65	1.0	1.0	1.1	1.1
Laser Diode [LS99]	0.31	0.45	0.39	2.2	1.2
Transistor [Moo06]	0.48	0.84	0.82	1.4	1.2

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