Innovation Diffusion with the Bass Model: Dreame Pocket High-Speed Hair Dryer (U.S.)

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October 05, 2025

```
knitr::opts_chunk$set(echo = TRUE, message = FALSE, warning = FALSE)
suppressPackageStartupMessages({
  library(tidyverse)
  library(readxl)
  library(ggplot2)
  library(broom)
})
```

2)

Historical analogue is the Dyson Supersonic (launched 2016) which covered the premium, high-speed dryer segment with a compact digital motor, intelligent heat control and magnetic attachments. Both innovations deliver fast drying from very high-velocity airflow generated by compact brushless motors and reduce heat damage via improved temperature control and ionization. Technologically, the Dreame Pocket inherits the high-RPM motor lineage while also having portability and 2-in-1 use (dry + style) in a folding form factor. Dyson re-created hair dryers as tech appliances consumers will pay a premium for and Dreame extends that premium proposition to travel and multifunction potentially enlarging the addressable premium niche by targeting on-the-go users.

3) Time series used: U.S. retail unit sales of hair dryers, 2010–2018 (millions). Statista. (2019). Retail unit sales of hair dryers in the United States from 2010 to 2018 (in millions). We use U.S. retail unit sales (2010–2018), U.S. household counts, and a U.S. launch context for Dreame.

```
hd <- read_excel("data/Hair-Dryer.xlsx") %>%
  mutate(Year = as.integer(Year),
         Sales = as.numeric(Sales)) %>%
  arrange(Year) %>%
  mutate(t = row_number())

hd
```

```
## # A tibble: 9 x 3
##    Year Sales     t
##   <int> <dbl> <int>
## 1  2010  21       1
## 2  2011  21       2
## 3  2012  20.7     3
## 4  2013  19.6     4
## 5  2014  19.4     5
## 6  2015  19.2     6
## 7  2016  19       7
## 8  2017  19.4     8
## 9  2018  19.3     9
```

```
ggplot(hd, aes(x = Year, y = Sales)) +
  geom_col() +
  labs(title = "U.S. Hair Dryer Retail Unit Sales (2010-2018)",
       y = "Units (millions)", x = NULL)
```

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Sales are around ~19–21 million units per year with a mild downward drift. This stability signals that current volumes are driven mostly by replacement purchases, not fresh first-time adoption. This is important to know when fitting the Bass model

Bass model: F(t) = M * (1 - exp(-(p+q)*t)) / [1 + (q/p)*exp(-(p+q)*t)]

```
bass_F <- function(t, p, q) {
  (1 - exp(-(p+q)*t)) / (1 + (q/p) * exp(-(p+q)*t))
}

bass_a <- function(t, p, q, M) {
  A_t   <- M * bass_F(t, p, q)
  A_tm1 <- M * bass_F(pmax(t-1, 0), p, q)
  A_t - A_tm1
}
```

These functions implement the Bass model in closed form. We use them to compute cumulative adoption for estimation and forecasting.

```r
start_free <- list(p = 0.01, q = 0.10, M = 200)
fit_free <- nls(Sales ~ bass_a(t, p, q, M),
                data = hd,
                start = start_free,
                algorithm = "port",
                lower = c(0, 0, 0))
summary(fit_free)
```

```
##
## Formula: Sales ~ bass_a(t, p, q, M)
##
## Parameters:
##    Estimate Std. Error t value Pr(>|t|)
## p 1.310e-02  9.535e-02   0.137    0.895
## q 0.000e+00  1.073e-01   0.000    1.000
## M 1.606e+03  1.172e+04   0.137    0.895
##
## Residual standard error: 0.4617 on 6 degrees of freedom
##
## Algorithm "port", convergence message: relative convergence (4)
```

```r
coef(fit_free)
```

```
##            p            q            M
## 1.309888e-02 0.000000e+00 1.606016e+03
```

The free-M as q approaches to 0 it inflates M to very large values which is a known signal in saturated markets where sales mainly reflect replacements. This fit can match levels but is hard to interpret economically so we treat it as a diagnostic rather than our primary specification.

```r
M_fix <- 130
start_fixed <- list(p = 0.015, q = 0.005)
fit_fixed <- nls(Sales ~ bass_a(t, p, q, M_fix),
                 data = hd,
                 start = start_fixed,
                 algorithm = "port",
                 lower = c(0, 0))
summary(fit_fixed)
```

```
##
## Formula: Sales ~ bass_a(t, p, q, M_fix)
##
## Parameters:
##   Estimate Std. Error t value Pr(>|t|)
## p  0.08291    0.04550   1.822    0.111
```

```
## q  0.35943    0.22964   1.565    0.162
##
## Residual standard error: 8.667 on 7 degrees of freedom
##
## Algorithm "port", convergence message: relative convergence (4)
```

```r
coef(fit_fixed)
```

```
##          p          q
## 0.08291297 0.35943336
```

Fixing M near U.S. household count yields small p and even smaller q which is consistent with the result we have for late diffusion tail. This produces more interpretable parameters for carrying over to the Dreame sub-segment forecast.

```r
hd_fit <- hd %>%
  mutate(pred_free  = bass_a(t, coef(fit_free)[["p"]],  coef(fit_free)[["q"]],  coef(fit_free)
         pred_fixed = bass_a(t, coef(fit_fixed)[["p"]], coef(fit_fixed)[["q"]], M_fix))

hd_fit_long <- hd_fit %>%
  select(Year, Sales, pred_free, pred_fixed) %>%
  pivot_longer(-Year, names_to = "series", values_to = "value")

ggplot(hd_fit_long, aes(Year, value, color = series)) +
  geom_point() + geom_line() +
  geom_col(data = hd, aes(Year, Sales), inherit.aes = FALSE, alpha = 0.2) +
  labs(title = "Observed vs. Bass Fits (Free M vs. Fixed M130M)",
       y = "Units (millions)", x = NULL, color = NULL)
```

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Both cases track the relatively flat observed sales but the fixed-M curve avoids unrealistic market-potential inflation.

A conservative U.S. market potential for the Dreame Pocket can be set at 6 million households. The U.S. has about 132.7 million households (2024 ACS), and a Statista price-expectations survey reports that only ~6.1% of consumers are willing to pay $100+ for a hair dryer—i.e., roughly 8.1 million premium-intent households at the category level. Because Dreame Pocket targets a compact/travel sub-segment within that premium tier and some of those buyers will choose full-size models or other brands. We adopt a conservative base = 6,000,000 for forecasting, which sits comfortably within the 5–8 million range implied by these data.

```r
p_hat <- as.numeric(coef(fit_fixed)[["p"]])
q_hat <- as.numeric(coef(fit_fixed)[["q"]])

M_dreame <- 6
horizon <- 20
years <- 1:horizon

dreame_new <- bass_a(years, p_hat, q_hat, M_dreame)
dreame_cum <- cumsum(dreame_new)

dreame_df <- tibble(
  Year = seq(2025, by = 1, length.out = horizon),
  New_Adopters_mln = dreame_new,
  Cumulative_Adopters_mln = dreame_cum
)

dreame_df %>% head(10)
```

```
## # A tibble: 10 x 3
##     Year New_Adopters_mln Cumulative_Adopters_mln
##    <dbl>            <dbl>                   <dbl>
##  1  2025            0.567                   0.567
##  2  2026            0.696                   1.26
##  3  2027            0.788                   2.05
##  4  2028            0.812                   2.86
##  5  2029            0.761                   3.62
##  6  2030            0.651                   4.27
##  7  2031            0.516                   4.79
##  8  2032            0.384                   5.17
##  9  2033            0.273                   5.45
## 10  2034            0.188                   5.64
```

We transfer the category's tail parameters (p,q) as a conservative baseline for Dreame, reflecting minimal imitation effects. The base market potential for the premium travel/compact segment is set to =6 million U.S. adopters over the product lifetime (which was analyzed before this step).

```r
p1 <- ggplot(dreame_df, aes(Year, New_Adopters_mln)) +
  geom_line() + geom_point() +
  labs(title = "Dreame Pocket - New Adopters per Year (U.S.)",
       y = "Millions", x = NULL)
p1
```

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```r
p2 <- ggplot(dreame_df, aes(Year, Cumulative_Adopters_mln)) +
  geom_line() + geom_point() +
  labs(title = "Dreame Pocket - Cumulative Adopters (U.S.)",
       y = "Millions", x = NULL)

p2
```

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Early years show modest new adoption that tapers gradually, while cumulative adoption increases steadily. With tiny q, the path lacks a sharp S-curve peak and instead reflects slow, persistent uptake within the premium niche.

```r
dreame_df %>%
  mutate(New_Adopters = round(New_Adopters_mln * 1e6),
         Cumulative_Adopters = round(Cumulative_Adopters_mln * 1e6)) %>%
  select(Year, New_Adopters, Cumulative_Adopters) %>%
  knitr::kable(format = "simple", align = "r")
```

Year	New_Adopters	Cumulative_Adopters
2025	566608	566608
2026	696238	1262846
2027	787657	2050503
2028	811934	2862437
2029	760538	3622975
2030	651112	4274087
2031	515863	4789950
2032	384180	5174130
2033	273126	5447257
2034	187826	5635083
2035	126231	5761314
2036	83531	5844845
2037	54709	5899554
2038	35591	5935146
2039	23052	5958198
2040	14889	5973087
2041	9598	5982685
2042	6180	5988865
2043	3977	5992842
2044	2557	5995399

New adopters peak immediately and then decline slowly which is the Bass model's expected pattern when imitation is weak. This implies predictable and non-spiky demand.

```r
M_grid <- c(4, 6, 8)
sens <- map_df(M_grid, function(Mi) {
  tibble(
    M = Mi,
    t = years,
    new = bass_a(years, p_hat, q_hat, Mi),
    cum = cumsum(bass_a(years, p_hat, q_hat, Mi))
  )
})

ggplot(sens, aes(t + 2024, cum, color = factor(M))) +
  geom_line(size = 1) +
  labs(title = "Cumulative Adopters - Sensitivity to Market Potential (U.S.)",
       subtitle = "M in millions; p, q from category tail (fixed-M fit)",
       y = "Millions", x = NULL, color = "M (mln)")
```

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Higher M shifts the curve upward but preserves the shape because p and q are unchanged. This illustrates that uncertainty about addressable market size mainly affects the level of adoption, not the dynamics under low imitation.