Supporting Information

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SI Text

Study 1. French Data. The data are quite comprehensive, but for privacy purposes, names that receive only a handful of births are omitted. The dataset is broken up into 2 recording periods. From 1900 to1945, the number of births with a name is recorded each year if (*i*) the name was given to at least 3 males or 3 females that year or (*ii*) the name was given to at least 20 males or females over the entire period. The same is true from 1946 to 2004. Because they are separate cultural items, we treat names as gender specific: If a first name is used both for girls and boys, we treat the 2 corresponding trajectories as if they were evolutions of different names. All variables and analyses are calculated relative to these gender-specific versions of each name. Similarly, given that parents not only select a name, but a particular spelling as well, we treat similar spellings of the same name as separate cultural items.

If not otherwise noted, the analyses treat names as abandoned when the percentage of all births in a year accounted by that name first reaches a level lower than 10% of its past maximum. A survivor plot (Fig. S1) illustrates that, with this measure, approximately half of the names are abandoned within 40 years of their entry in the dataset. This measure has the advantage of not relying on future information and allows us to avoid estimation problems related to right censoring. Results are similar when other thresholds (e.g., 5% or 20%) are used (Table S2, Model 10). We use a relative threshold for our main analyses because it more effectively deals with the effect of popularity. A fixed threshold of (e.g., 10 births a year) is somewhat problematic because a name that has peaked higher (e.g., 1,000 versus 100 births a year) will likely take more time to reach that threshold. Using a relative threshold should alleviate the effect of the size of the peak in popularity on the dependent variable.

Table S1 displays the main results. The effect of adoption velocity is robust to alternate ways of controlling for the effect of age (Models 2 and 3). In Model 3, we include the number of years elapsed since the occurrence of the past maximum frequency as well as the "weighted age" of a name. This latter quantity is defined as the average number of years elapsed between births with name *i* and the focal year, computed over all past births with name *i*. If name *i* was very popular recently, its weighted age is low, whereas, if name *i* was very popular in the distant past, its weighted age is high. The effect of adoption velocity remains strong even after accounting for timing effects in this more refined way.

We also demonstrate that these effects are not driven by a handful of names that shoot up due to appearance in mass entertainment (e.g., prominent performers) but then die out when the performers disappear from public attention. Model 4 uses dummy variables for adoption velocity equal to 1 if adoption velocity is in the corresponding quartile and zero otherwise. Estimates suggest that even moderate level of adoption velocity have a positive effect on the hazard of death.

The effect of adoption velocity is also robust to different ways of calculating the rate of change in popularity. For example, computing it over longer windows such as 15 years (Model 5) or if a 5-year lag is introduced (Model 6) does not change the main result. It is worth noting that longer time windows provide more accurate estimates of the overall adoption velocity and also result in larger effect sizes. Although this result supports our perspective, using larger windows and/or longer lags reduces the number of at-risk observations; hence, we use a moderately sized window of 5 years for the main analyses.

Additional model estimations are reported in Table S2. Model 7 includes dummy variables for the each year (but not for 1900–1910 and 1912 because of the colinearity issues that the inclusion of those dummies would create). This allows for a good control of period effects. Our main result still holds with this specification (for brevity, the coefficient estimates of the year dummies are not reported here). Models 8 and 9 show that the result holds when a proportional hazard rate model (Cox model) is used with either Breslow or Efron methods to handle ties. These model specifications are useful as robustness checks because they provide good control for aging effect. Finally, we estimated a model similar to Model 3 in Table S1 on gender-specific data (Table S2, Models 11 and 12). This analysis demonstrates that the effect of adoption velocity persists across genders and is strongly significant for both male and female names.

Further analysis designed to study the evolution of the effect of adoption velocity over the period covered did not lead to robust conclusions. Estimation of models including an interaction term (Adoption Velocity × Year or Adoption Velocity × Year of Past Max Frequency) suggest that the effect of adoption velocity might be stronger in later years, but this finding is not very robust to alternate specifications.

Table S4 reports OLS estimations of the logarithm of the cumulative number of births with a given name before abandonment. Results show that the negative relation between adoption velocity and cumulative number of births with a given first name is robust to the inclusion of control variables such as maximal popularity of a name and controls about timing and aging. Whereas the graph of Fig. 3 suggests that the relation between adoption velocity and cumulative adoption might be curvilinear, additional analyses suggest that the relation is monotonous and negative over most values of adoption velocity (i.e., if there is nonmonotonicity, it is driven by the few observations with very low adoption velocity at time of maximal popularity).

U.S. Data. The estimation results are reported in Table S3. The relation between adoption velocity and death rate is strongly positive and significant, and it is robust to various ways of controlling for timing effects, including Cox proportional-hazard models. Results are also robust to lower threshold levels for inclusion such as 500 births per year. Overall, the results are almost identical to those found in the French name data. Both suggest that names that are adopted faster tend to die more quickly.

Study 2. Names were selected according to a variety of constraints. Given our interest in how increases in usage influence adoption likelihood, we selected names that were still increasing in popularity based on the last year of data available at the time of the study (2006). Certain names have multiple spellings, each with different levels of popularity, and some are given to both males and females. This creates difficulties when matching ratings with actual popularity change, so we avoided this problem by only using names with a single spelling which appeared in the top 1,000 names for only one gender. Furthermore, given that many ethnic names may be localized among certain racial groups, we avoided names with strong links to specific minority groups.

Ancillary results also cast doubt on an alternative explanation based on popularity perceptions. One could argue that names with sharper increases in adoption could be perceived as more popular, and that this perceived popularity, rather than fad perceptions, could be driving reduced adoption likelihood. Additional data collected from the expecting parents, however, shows that this is not the case. After participants rated fad perceptions, we also had them rate how popular they perceived each name to be. Adoption velocity was positively related to perceived popularity; names that had sharper increases in popularity were perceived as more popular, even controlling for the actual popularity of the name. The relationship between perceived popularity and adoption likelihood, however, was positive. Participants said they would be more likely to adopt names that they thought were more popular. Given that the names used were still increasing in adoption, the popularity levels may not yet have been high enough to have a negative effect, but these analyses indicate that popularity perceptions were not driving reduced adoption likelihood in this instance.

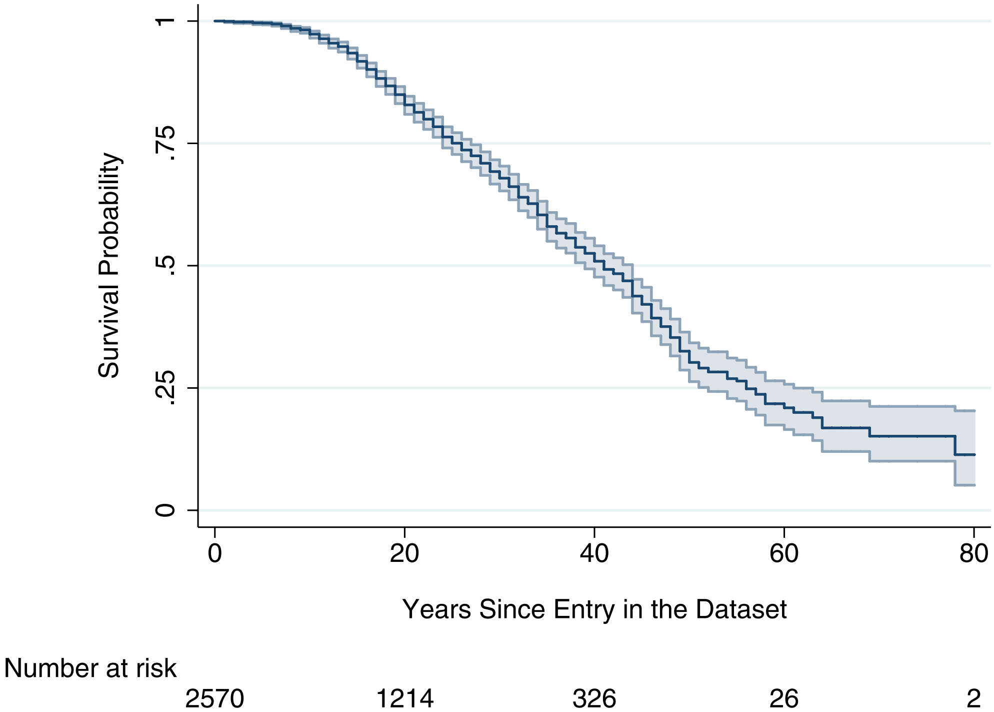

Fig. S1. Kaplan–Meier estimates of the survivorship function of the first names with 95% confidence intervals.

Table S1. Hazard-rate model estimations of name death (French data)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender dummy (1 if female name, 0 if male name)	0.43*** (0.08)	0.40*** (0.08)	0.34*** (0.08)	0.35*** (0.08)	0.43*** (0.08)	0.52*** (0.09)
Years at risk, y	0.05*** (0.00)	0.05*** (0.00)				
Cumulative frequency at $y-1$	−0.49*** (0.13)	−0.43** (0.13)	−0.35** (0.12)	−0.33** (0.12)	−0.42*** (0.12)	−0.50*** (0.13)
Past max frequency ($F_{i,Y_{t,y}}$)	0.46*** (0.12)	0.39*** (0.12)	0.49*** (0.11)	0.45*** (0.11)	0.53*** (0.10)	0.59*** (0.10)
Adoption velocity ($\alpha_{i,y}$)		1.40*** (0.21)	1.18*** (0.21)		1.24*** (0.21)	3.74*** (0.63)
$y - Y_{i,t}$			0.05*** (0.01)	0.06*** (0.01)	0.04*** (0.01)	0.04*** (0.01)
Weighted age of the name at $y - 1$			0.08*** (0.01)	0.08*** (0.01)	0.09*** (0.01)	0.11*** (0.01)
$F_{i,Y_{t,y}}$ in second quartile				0.23* (0.11)		
$F_{i,Y_{t,y}}$ in third quartile				0.39*** (0.11)		
$F_{i,Y_{t,y}}$ in fourth quartile				0.60*** (0.11)		
Constant	−5.54*** (0.09)	−5.90*** (0.11)	−6.48*** (0.13)	−6.57*** (0.14)	−6.77*** (0.14)	−7.43*** (0.19)
χ^2	416.43	454.99	1018.07	1019.67	959.19	850.36
Log likelihood	−1,323.51	−1,304.23	−1,022.68	−1,021.88	−894.55	−711.21
Name–year observations	52,693	52,693	52,693	52,693	40,067	47,665
First names	2,570	2,570	2,570	2,570	1,987	2,420
Death events	701	701	701	701	517	626

Adoption velocity is computed between $Y_{i,y} - 5$ and $Y_{i,y}$ for models 1, 2, 3, and 4 (see legend of Fig. 2 in the main paper), between $Y_{i,y} - 15$ and $Y_{i,y}$ for model 5, and between $Y_{i,y} - 10$ and $Y_{i,y} - 5$ for model 6. Results indicate that, even controlling for other factors, sharper increases in popularity are linked to faster death. Rather than using adoption velocity, Model 4 uses dummy variables equal to 1 if the adoption velocity is in the corresponding quartile and 0 otherwise. Estimates show that the size of the effect of adoption velocity increases as adoption velocity becomes larger. *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$.

Table S2. Hazard rate model estimations of name death with French data (continued)

Variables	Model 7 (includes year dummies)	Model 8 (Cox proportional-hazard model, Bradlow method)	Model 9 (Cox proportional-hazard model, Efron method)	Model 10 (abandonment threshold at 1% of past max frequency)	Model 11 (male names)	Model 12 (female names)
Gender dummy (1 if female name, 0 if male)	0.31*** (0.08)	0.35*** (0.08)	0.35*** (0.08)	0.48*** (0.1)		
Cumulative frequency at $y-1$	−0.34** (0.12)	−0.23* (0.11)	−0.22 (0.12)	−1.45*** (0.25)	−0.35 (0.22)	−0.46** (0.08) (−0.16)
Past max frequency ($F_{i,Y_{t,y}}$)	0.47*** (0.11)	0.43*** (0.11)	0.42*** (0.11)	1.14*** (0.17)	0.46* (0.19)	0.61*** (−0.15)
Adoption velocity ($\alpha_{i,y}$)	1.22*** (0.21)	1.15*** (0.22)	1.14*** (0.22)	0.81** (0.28)	2.18*** (0.35)	0.75** (−0.26)
$y - Y_{i,t}$	0.06*** (0.01)	0.07*** (0.01)	0.07*** (0.01)	0.02*** (0.01)	0.07*** (0.01)	0.04*** (−0.01)
Weighted age of the name at $y-1$	0.09*** (0.01)	0.11*** (0.01)	0.11*** (0.01)	0.08*** (0.01)	0.07*** (0.01)	0.08*** (−0.01)
Constant	−22.41 (24,455.72)			−6.77*** (0.15)	−6.86*** (0.21)	−6.01*** (−0.15)
χ^2	1234.93	751.49	731.93	777.59	443.24	583.82
d.f.	100			7	6	6
Log-likelihood	−914.2532	−4,233.346	−4,251.182	−835.8631	−403.3954	−605.538
Name–year observations	52,693	52,693	52,693	57,480	24,158	28,535
First names	2,570	2,570	2,570	2,570	1,132	1,438
Death events	701	701	701	932	265	436

Adoption velocity is computed between $Y_{i,y} - 5$ and $Y_{i,y}$. Model 7 controls for period effects by including year dummies for almost all years (some dummies are dropped because of colinearity; dummy estimates are not reported here). Models 8 and 9 show results of Cox proportional-hazard models. Results are similar to those of the baseline model (Model 3 in Table S1). Model 10 uses a different abandonment threshold (1% of the past maximal frequency). Models 11 and 12 are the baseline model with gender-specific data. The effect of adoption velocity is positive and significant for names of both genders. *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$.

Table S3. Hazard models of name death (U.S. data)

Variables	Model 1	Model 2	Model 3
Gender dummy (1 if female name, 0 if male name)	0.79*** (0.19)	0.74*** (0.19)	0.99*** (0.19)
Years at risk, y	0.06*** (0.00)	0.06*** (0.00)	−0.03* (0.01)
Cumulative frequency at $y-1$	−1.89*** (0.23)	−1.80*** (0.23)	−1.23*** (0.24)
Past max frequency ($F_{i,Y_{t,y}}$)	1.26*** (0.14)	1.20*** (0.14)	1.15*** (0.16)
Adoption Velocity ($\alpha_{i,y}$)		1.44** (0.50)	1.32* (0.56)
$y-Y_{i,t}$			0.05*** (0.01)
Weighted age of the name at $y-1$			0.10*** (0.02)
Constant	−5.75*** (0.25)	−6.02*** (0.27)	−7.01*** (0.33)
χ^2	301.95	309.05	379.88
Log likelihood	−170.6277	−167.0756	−131.6638
Name–year observations	12,514	12,514	12,514
First names	477	477	477
Death events	189	189	189

Adoption velocity is computed between $Y_{i,y}-5$ and $Y_{i,y}$. Results indicate that even controlling for other factors, sharper increases in popularity are associated to faster abandonment. *, $P<0.05$; **, $P<0.01$; ***, $P<0.001$.

Table S4. OLS estimation of the log of the cumulative number of births with a given name prior to abandonment (French data)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Log(years at risk): Log(y)	0.75*** (0.02)	0.67*** (0.02)			
Log(past max frequency): Log($F_{i,Y_{t,y}}$)	0.88*** (0.01)	0.89*** (0.01)	1.00*** (0.01)	1.00*** (0.00)	
Log(adoption velocity at $Y_{i,t}$): Log($\alpha_{i,y}$)		−0.11*** (0.01)	−0.10*** (0.01)	−0.24*** (0.02)	−0.35*** (0.06)
Log($\alpha_{i,y}$)^2				−0.03*** (0.00)	
Log($y - Y_{i,t}$)			0.07* (0.03)	0.08** (0.03)	
Log(weighted age of the name at $y - 1$)			0.89*** (0.04)	0.84*** (0.04)	
Constant	7.12*** (0.07)	7.17*** (0.07)	6.84*** (0.06)	6.80*** (0.06)	6.61*** (0.13)
Log likelihood	−30.30	31.67	153.11	153.11	−1,276.28
R^2	0.97	0.98	0.98	0.98	0.05

Each observation is a unique first name that was abandoned during the period of observation. Names that experience sharper increases in adoption achieve lower overall usage. *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; 701 observations (first-names death events).