Online Appendix for

"Eponymous Entrepreneurs"

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This appendix has three parts. §A contains formal analysis and proofs for the model. Additional results are also derived. §B describes our methodology for identifying eponymous firms, and shows our results are robust to alternative methods. §C contains additional empirical results and robustness checks.

§A Formal Analysis of the Model

Preliminaries

We note three properties of the sender's expected payoff function, u_θ: i) u_θ is differentiable in both of its arguments; ii) $\frac{\partial u_\theta}{\partial \mu} > 0$; iii) $u_H(s,\mu) \geq u_L(s,\mu)$ for any (s,μ), and the inequality is strict if and only if $\mu \in (0,1)$. Property (i) is immediate. To see (ii), let V_1, V_2 be the sender's first- and second-period payoff functions, respectively. Note that

$$u_H(s,\mu_1) = V_1(\mu_1) + pV_2(s,\mu_2(\mu_1,h)) + (1-p)V(s,\mu_2(\mu_1,l)).$$

Therefore,

$$\frac{\partial u_H}{\partial \mu_1} = \frac{\partial V_1}{\partial \mu_1} + p\frac{\partial V_2}{\partial \mu_2}\frac{\partial \mu_2(\mu_1,h)}{\partial \mu_1} + (1-p)\frac{\partial V_2}{\partial \mu_2}\frac{\partial \mu_2(\mu_1,l)}{\partial \mu_1}.$$

Using the expressions for V_1, V_2, and Bayes rule for μ_2, we get

$$\frac{\partial V_1}{\partial \mu_1} = 2p-1 > 0, \qquad \frac{\partial \mu_2(\mu_1,h)}{\partial \mu_1} = \frac{(1-p)p}{(1-p-\mu_1+2p\mu_1)^2} > 0,$$

$$\frac{\partial V_2}{\partial \mu_2} = s(1+\gamma) > 0, \qquad \frac{\partial \mu_2(\mu_1,l)}{\partial \mu_1} = \frac{(1-p)p}{(p+\mu_1-2p\mu_1)^2} > 0,$$

which imply the result when $\theta = H$. A symmetric argument holds for $\theta = L$. For (iii), see that

$$u_H(s,\mu_1) - u_L(s,\mu_1) = (2p-1)\big(V_2(s,\mu_2(\mu_1,h)) - V_2(s,\mu_2(\mu_1,l))\big) = \frac{(1+\gamma)(1-2p)^2 s(1-\mu_1)\mu_1}{(\mu_1-\mu_1^2)+(p-p^2)(2\mu_1-1)^2}.$$

It is clear that the numerator is positive for all $\mu_1 \in (0,1)$ and zero when $\mu_1 = 0,1$. Because $p \in (\frac{1}{2},1)$, the detonator is positive for all $\mu_1 \in [0,1]$, giving the result.

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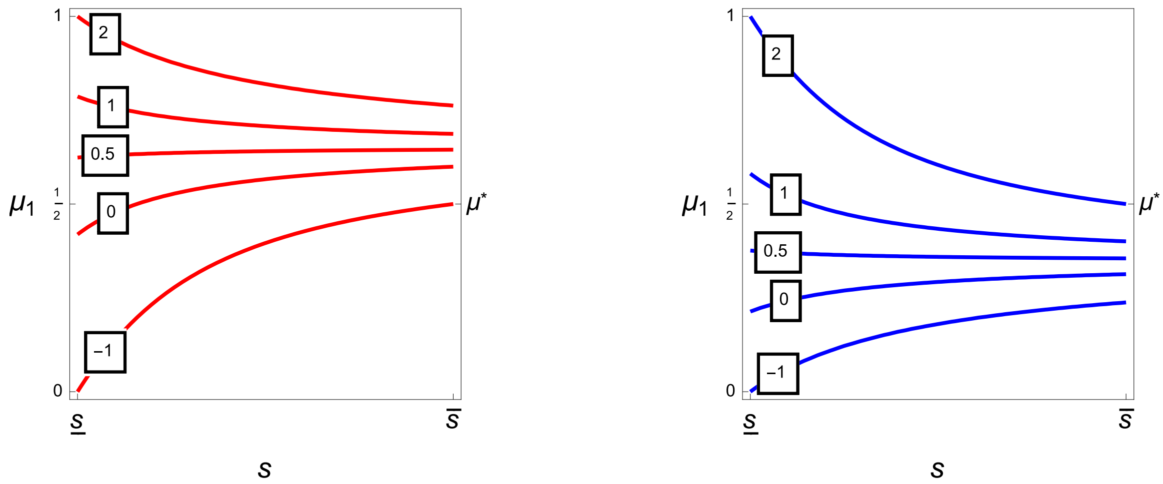


(a) Low type

(b) High type

Figure A1: Plots of (s, μ_1)-indifference curves for expected-payoff levels $\{-1, 0, \frac{1}{2}, 1, 2\}$ using $p = \frac{3}{4}$, $\gamma = 1$, $\underline{s} = \frac{5}{4}$, and $\overline{s} = 6$.

Sender (s, μ_1)-Indifference Curves and Single-Crossing

Define $b_\theta(s|\hat{u})$ to be the unique belief level satisfying $u_\theta(s, b_\theta(s|\hat{u})) = \hat{u}$. That is, $b_\theta(\cdot|\hat{u})$ represents the type-θ sender's (s, μ_1)-indifference curve as a function from signaling level to first-period belief, holding fixed the expected payoff level $\hat{u}$. Notice that since u_θ is differentiable in both arguments, b_θ is differentiable as well.

Figure A1 depicts the entrepreneur's (s, μ_1)-indifference curves. Regardless of type, for any fixed s, expected payoff is increasing in μ_1. However, for fixed μ_1, expected payoff is increasing in s if and only if μ_1 is sufficiently large, which is the manifestation of the assumption that a larger s increases the reputational benefits or costs of the market's impression. In the extremes, the best outcome for the entrepreneur is to have chosen the maximal s coupled with the market being convinced she is high ability, whereas the worst outcome also involves having chosen the maximal s but coupled with the market being convinced she is low ability.

Comparing the indifference curves of the two types, first, there is a difference in levels: the indifference curves for the low type (panel (a)) are shifted up compared to those of the high type (panel (b))—as we demonstrated above, $u_H(s, \mu_1) > u_L(s, \mu_1)$ for all $\mu_1 \in (0, 1)$. This difference arises because the market will learn based on the realized quality of first-period output, g. In expectation, this learning hurts the low type and helps the high type. Second, the slopes of the indifference curves for the two types differ at every point (s, μ_1). That is, the types differ not only in their payoff levels, but also in terms of the marginal expected payoff they derive from s and μ_1. In particular, we now demonstrate that (s, μ_1)-indifference curves satisfy the *single-crossing property.*

Let $\hat{u}$ denote an arbitrary expected-payoff level and $\mu_1(s) = b_\theta(s|\hat{u})$. Then, by definition, $u_\theta(s, \mu_1(s)) = \hat{u}$. Total differentiation of both sides with respect to s gives $\frac{\partial u_\theta}{\partial s} + \frac{\partial u_\theta}{\partial \mu_1}\frac{\partial \mu_1}{\partial s} = 0$.

Hence,

$$\frac{\partial \mu_1}{\partial s} = \frac{\partial b_\theta}{\partial s} = -\frac{\partial u_\theta}{\partial s} \Big/ \frac{\partial u_\theta}{\partial \mu_1}.$$

For single-crossing, we need $\frac{\partial b_L}{\partial s} > \frac{\partial b_H}{\partial s}$. Direct calculation yields $\frac{\partial b_L}{\partial s} - \frac{\partial b_H}{\partial s}$ can be expressed as the product of four terms (denoted $T_1 \cdot T_2 \cdot T_3 \cdot T_4$), each of which is positive for all $\gamma, s > 0$, $p \in (\frac{1}{2}, 1)$, and $\mu_1 \in [0, 1]$:

$$T_1 \equiv (1+\gamma)(2p-1)^2 \big(p(1-\mu_1) + \mu_1(1-p)\big)^2 \big(1 - p(1-\mu_1) - \mu_1(1-p)\big)^2$$

$$T_2 \equiv \gamma \left(p(1-p)s\mu_1^2\right) + s \left(p(1-p)(1-\mu_1)^2\right) + (2p-1)\mu_1(1-\mu_1) \left(p(1-p)(1-2\mu_1)^2 + \mu_1(1-\mu_1)\right)$$

$$T_3 \equiv \frac{1}{s(1+\gamma)p(1-p)\left((2p-1)^2\mu_1^2 + p(1-p)\right) + (2p-1)\left(p(1-p)(1-2\mu_1)^2 + \mu_1(1-\mu_1)\right)^2}$$

$$T_4 \equiv \frac{1}{s(1+\gamma)p(1-p)\left(p(1-p)(2\mu_1-1)(3-2\mu_1) + (1-\mu_1)^2\right) + (2p-1)\left(p(1-p)(1-2\mu_1)^2 + \mu_1(1-\mu_1)\right)^2}$$

Hence, the (s, μ_1)-indifference curves satisfy the single-crossing property as claimed in Section 1.

The D1 Refinement

In our model, the D1 refinement can be stated as follows. Fix an equilibrium endowing expected payoffs $\{u_L^*, u_H^*\}$. Consider a signal s that is not in the support of either type's strategy. Define $B_\theta(s, u_\theta^*) \equiv \{\mu_1 : u_\theta(s, \mu_1) > u_\theta^*\}$. If $B_L(s, u_L^*) \subset B_H(s, u_H^*)$, then D1 requires that $\mu_1(s) = 1$ (where $\subset$ denotes strict inclusion). If $B_H(s, u_H^*) \subset B_L(s, u_L^*)$, then D1 requires that $\mu_1(s) = 0$. The interpretation of the refinement is that if, for a deviant s, type θ has a strictly larger B_θ (in sense of set inclusion) than type θ', then receivers should believe that the deviator is of type θ.[1]

Proof of Proposition 1

The proof consists of three parts: i) verifying that the proposed profiles are equilibria; ii) verifying that they satisfy D1; and iii) demonstrating that no other equilibria satisfy D1.

Part (i): For the first case, fix $\mu_0 \geq \mu^*$. The proposed strategies are full pooling on $\overline{s}$. The belief $\mu_1(\overline{s}) = \mu_0$ is therefore consistent with the strategy profile. If the sender deviates to $s \in [\underline{s}, \overline{s})$, the belief is $\mu_1(s) = 0$. Recall that u_θ is increasing in μ_1 and nondecreasing in θ, and that $u_L(\overline{s}, \mu^*) = (1-p) - \underline{s}$. Therefore, deviating to $s \neq \overline{s}$ leads to $u_\theta(s, 0) = (1-p) - s \leq (1-p) - \underline{s} = u_L(\overline{s}, \mu^*) \leq u_L(\overline{s}, \mu_0) \leq u_H(\overline{s}, \mu_0)$, where the last two terms are the low- and high-type equilibrium expected payoff levels, respectively. Hence, there is no incentive to deviate, establishing that this is an equilibrium. For the second case, fix $\mu_0 < \mu^*$. The proposed strategies are partial pooling with the high type selecting $\overline{s}$ and the low type mixing between $\underline{s}$ and $\overline{s}$, selecting $\overline{s}$ with probability

[1] See Daley and Green (2014) for further discussion, including the equivalence (in this class of models) between this definition and D1's original definition (Banks and Sobel, 1987; Cho and Kreps, 1987).

$\frac{\mu_0(1-\mu^*)}{\mu^*(1-\mu_0)}$. From Bayes rule, the on-path beliefs $\mu_1(0) = 0$ and

$$\mu_1(\overline{s}) = \frac{\mu_0}{\mu_0 + (1-\mu_0)\frac{\mu_0(1-\mu^*)}{\mu^*(1-\mu_0)}} = \mu^*$$

are consistent with the strategies. By definition of μ^*, $u_L(\underline{s}, 0) = u_L(\overline{s}, \mu^*)$, so the low type is indeed indifferent between $\underline{s}$ and $\overline{s}$ as required by her mixing. Further, $\mu_1(s) = 0$ for all $s \neq \overline{s}$. Hence, just as above, any deviation to a signal s leads to a payoff of $u_\theta(s, 0) = (1-p) - s \leq (1-p) - \underline{s} = u_L(\overline{s}, \mu^*) \leq u_H(\overline{s}, \mu^*)$, where the last two terms are the low- and high-type equilibrium expected payoff levels respectively. Hence, there is no incentive to deviate, establishing that this is an equilibrium.

Part (ii): To see that the equilibrium satisfies D1 in both of the above cases, for either case, let $\{u_L^*, u_H^*\}$ be the equilibrium expected payoffs. Notice that $b_L(\overline{s}|u_L^*) = b_H(\overline{s}|u_H^*)$. Therefore, single-crossing implies that $b_L(s|u_L^*) < b_H(s|u_H^*)$ for all $s \in [\underline{s}, \overline{s})$. Finally, note that because u_θ is increasing in μ_1, $B_\theta(s, u_\theta^*) = \{\mu_1 : 1 \geq \mu_1 > b_\theta(s|u_\theta^*)\}$. Therefore, $b_L(s|u_L^*) < b_H(s|u_H^*)$ for all $s \in [\underline{s}, \overline{s})$ implies that $B_H(s, u_H^*) \subset B_L(s, u_L^*)$ for all $s \in [\underline{s}, \overline{s})$. Hence, D1 requires that $\mu_1(s) = 0$ for all off-path $s \in [\underline{s}, \overline{s})$, which is precisely what the equilibrium specifies.

Part (iii): Let S_θ be the support of the type-θ sender's strategy. We first establish the following claim: in any equilibrium, if $s \in S_H$, then $\mu_1(s) < 1$. Suppose the claim were false, and there exists $s \in S_H$ such that $\mu_1(s) = 1$. Then $u_H^* = u_H(s, 1)$, and, because the low type has the option of selecting s as well, for any $s' \in S_L$, $u_L^* = u_L(s', \mu_1(s')) \geq u_L(s, 1)$. Further, $u_L(s, 1) > u_L(\tilde{s}, \mu_1)$ for any $\tilde{s} \leq s$ and $\mu_1 \in [0, 1]$. Hence, $s' > s$ for any $s' \in S_L$. But single-crossing implies that for any such $(s', \mu_1(s'))$ pair, $\mu_1(s') \in b_H(s'|u_H^*)$, meaning the high type prefers to deviate to s', contradicting the equilibrium.

Second claim: in any equilibrium, S_H is singleton and $S_L \subseteq \{\underline{s}\} \cup S_H$. Suppose instead that there was a distinct pair $s_1, s_2 \in S_H$. It must be then that $u_H(s_1, \mu_1(s_1)) = u_H(s_2, \mu_1(s_2))$. Also, by the first claim and the equilibrium belief consistency requirement, $\mu_1(s_1), \mu_1(s_2)$ are both in $(0, 1)$. This means $s_1, s_2 \in S_L$ as well, and therefore that $u_L(s_1, \mu_1(s_1)) = u_L(s_2, \mu_1(s_2))$. But this contradicts single-crossing, so cannot hold. Next, suppose there exists $s \in S_L$, but $s \notin S_H$. Then belief consistency requires that $\mu_1(s) = 0$. So, $u_L^* = u_L(s, 0) = (1-p) - s$. If $s > \underline{s}$, the low type would gain by selecting $\underline{s}$ instead, so it must be that $s = \underline{s}$, establishing the result.

Third claim: in any D1 equilibrium, $S_H = \{\overline{s}\}$. For the purpose of contradiction, suppose not, and that $S_H = \{s\}$, where $s \neq \overline{s}$. Then $u_H^* = u_H(s, \mu_1(s))$ and, because the low type has the option of selecting s as well, $u_L^* \geq u_L(s, \mu_1(s))$. Therefore, $b_H(s|u_H^*) \leq b_L(s|u_L^*)$. But then, by single-crossing, for $\epsilon > 0$ small enough, $b_H(s+\epsilon|u_H^*) < b_L(s+\epsilon|u_L^*)$, implying $B_L(s+\epsilon, u_H^*) \subset B_H(s+\epsilon, u_L^*)$. D1 requires that $\mu_1(s+\epsilon) = 1$, meaning the high type's payoff from deviating to $s+\epsilon$ is $u_H(s+\epsilon, 1) > u_H(s, \mu_1(s))$ for any $\mu_1(s) \in [0, 1]$. Because $u_H^* = u_H(s, \mu_1(s))$, the deviation is profitable, producing the contradiction.

Finally, from our second and third claims, in any D1 equilibrium, the low type's strategy can be summarized by the probability with which she selects $\overline{s}$, denoted by β (as she plays $\underline{s}$ with the complementary probability $1-\beta$). We now return to our two cases regarding μ_0. For the first case, fix $\mu_0 \geq \mu^*$. If $\beta < 1$, then by Bayes rule, it must be that $\mu_1(\underline{s}) = 0$ and $\mu_1(\overline{s}) > \mu_0 \geq \mu^*$. By definition of μ^* and u_L increasing in μ_1, we have $u_L(\overline{s}, \mu_1(\overline{s})) > u_L(\overline{s}, \mu^*) = u_L(\underline{s}, 0)$, meaning the low type strictly prefers $\overline{s}$ to $\underline{s}$, contradicting $\beta < 1$. Hence, $\beta = 1$, and the equilibrium is full pooling as described in the proposition. For the second case, fix $\mu_0 < \mu^*$. If $\beta = 1$, then by Bayes rule, it must be that $\mu_1(\overline{s}) = \mu_0 < \mu^*$. By definition of μ^* and u_L increasing in μ_1, we have $u_L(\overline{s}, \mu_1(\overline{s})) < u_L(\overline{s}, \mu^*) = u_L(\underline{s}, 0) \leq u_L(\underline{s}, \mu_1(\underline{s}))$ for all $\mu_1(\underline{s}) \in [0, 1]$, meaning the low type strictly prefers $\underline{s}$ to $\overline{s}$, contradicting $\beta = 1$. Similarly, if $\beta = 0$, then by Bayes rule, it must be that $\mu_1(\underline{s}) = 0$ and $\mu_1(\overline{s}) = 1 > \mu^*$, which means the low type would prefer $\overline{s}$ to $\underline{s}$ for the reason given in the first case above and generating a contradiction. Hence, $\beta \in (0, 1)$, meaning the low type is strictly mixing and must therefore be indifferent between $\underline{s}$ and $\overline{s}$. By Bayes rule, $\mu_1(\underline{s}) = 0$, so indifference requires that $u_L(\overline{s}, \mu_1(\overline{s})) = u_L(\underline{s}, 0)$. By definition, this is only satisfied when $\mu_1(\overline{s}) = \mu^*$. For this belief to be consistent with Bayes rule, it must be that $\beta = \frac{\mu_0(1-\mu^*)}{\mu^*(1-\mu_0)}$, as described in the proposition. *Q.E.D.*

Comparative Statics on μ^*

For Hypothesis 2 it is claimed that μ^* (which measures the average ability of eponymous entrepreneurs in equilibrium) is increasing in $\overline{s}$. To see this, solve $\frac{\partial b_L}{\partial s} = 0$ for μ_1 and obtain

$$\mu_1 = \overline{\mu} \equiv \frac{\gamma p^2 - \gamma p + 5p^2 - 5p + 1 + \sqrt{\left((\gamma+5)p^2 - (\gamma+5)p + 1\right)^2 + 4p(1-p)(1-2p)^2}}{2(1-2p)^2} \in (0, 1),$$

which is independent of s. Therefore, because u_L is continuous, either i) the low type's indifference curve is strictly increasing at every (s, μ_1) such that $\mu_1 < \overline{\mu}$, or ii) the low type's indifference curve is strictly decreasing at every (s, μ_1) such that $\mu_1 < \overline{\mu}$. To see that (i) is true, note that

$$\lim_{\mu_1 \to 0} \frac{\partial b_L}{\partial s} = \frac{1}{s(1+\gamma) + (2p-1)} > 0.$$

Finally, note that $u_L(\underline{s}, 0) < u_L(\underline{s}, \overline{\mu})$, so the two points reside on distinct low-type indifference curves, which by definition, do not intersect. Hence, by continuity of u_L, the low type's indifference curve for $u_L(\underline{s}, 0)$ (i.e., $b_L(s|u_L(\underline{s}, 0))$ is strictly increasing in s. By definition, $(\overline{s}, \mu^*)$ resides on this same indifference curve (i.e., $b_L(\overline{s}|u_L(\underline{s}, 0)) = \mu^*$), yielding the result. This comparative static is illustrated in Figure A1(a). There, $u_L(\underline{s}, 0) = (1-p) - \underline{s} = -1$, and the corresponding indifference curve $b_L(s|-1)$ is strictly increasing. Since $\mu^* = b_L(\overline{s}|-1)$, μ^* is increasing in $\overline{s}$.

We can also investigate how μ^* varies with the accuracy of market information, p, to generate additional predictions from the model.[2] To do so, see that the low type's expected second-period payoff is decreasing in p at a rate proportional to s: for $p_1 < p_2$,

$$E_g[V_2(s, \mu_2(\mu_1, g)|L, p_2] - E_g[V_2(s, \mu_2(\mu_1, g)|L, p_1] = \frac{s(1+\gamma)(1-\mu_1)\mu_1^2(p_2(1-p_2) - p_1(1-p_1))}{X(\mu_1, p_1)(1 - X(\mu_1, p_1))X(\mu_1, p_2)(1 - X(\mu_1, p_2))} < 0,$$

[2] Recall that p is the probability that the quality of the entrepreneur's first-period offering reflects her underlying ability and, therefore, serves as a measure of how accurately/quickly the market learns her ability. See footnote 7 of the main text for further discussion.

where, $X(\mu_1, p) \equiv p(1-\mu_1) + \mu_1(1-p) \in [(1-p), p] \subset (0,1)$ for all $p \in (\frac{1}{2}, 1)$ and $\mu_1 \in [0,1]$. The inequality holds because $p_2(1-p_2) - p_1(1-p_1) < 0$ for $\frac{1}{2} < p_1 < p_2 < 1$, while all other terms are positive. Hence, as long as $\overline{s}$ is sufficiently large (one interpretation of which is that the second period is sufficiently important to the entrepreneur's overall payoff—see footnote 7 of the main text), an increase in p decreases the low type's expected payoff from the partial-pooling signal, $\overline{s}$, necessitating an increase in the associated partial-pooling belief, $\mu_1(\overline{s}) = \mu^*$, to keep her indifferent between imitating the high type or not (recall from above that u_L is strictly increasing in μ_1).[3] Because V_2 is interpreted as a reduced-form modeling of the entrepreneur's long-run payoffs, it seems natural that it should indeed be sufficiently important, leading to the following:

Hypothesis 3 *As the accuracy of market information increases,*

- **(a)** *the performance difference between eponymous and non-eponymous firms increases (i.e., Hypothesis 1 is strengthened).*
- **(b)** *performance outcomes become more dispersed.*

In summary, if market information is more accurate, then low-ability entrepreneurs will find eponymy less attractive because unfavorable outcomes are now more likely for them. Hence, the performance difference between eponymous and non-eponymous firms will grow, and the distribution of performance outcomes will more accurately reflect underlying differences in ability.

Hypothesis 3(b) is then straightforward, using μ_2 to measure (long-run) performance. In the partial-pooling equilibrium, only three μ_2-values are reached with positive probability: $0 < \mu_2(\mu^*, l) < \mu_2(\mu^*, h)$. Hence, a simple measure of dispersion is the difference between the highest and the lowest of these, which is just $\mu_2(\mu^*, h)$.[4] When μ^* is increasing in p, so too is $\mu_2(\mu^*, h)$ because

$$\frac{\partial \mu_2(\mu_1, h)}{\partial p} = \frac{u(1-u)}{(p(2u-1)-u+1)^2} > 0, \qquad \frac{\partial \mu_2(\mu_1, h)}{\partial \mu_1} = \frac{p(1-p)}{(p(2u-1)-u+1)^2} > 0.$$

Our data do not allow a direct measure of the accuracy of market information. However, in §C, we will argue that industry variation in the eponymy-performance relationship and performance dispersion are consistent with this explanation—that is, plausibly attributable to differences in market information.[5]

[3] Notice that the payoff from *not* imitating the high type (i.e., $u_L(\underline{s}, 0)$) is also directly affected by p, but only in the first period. However, for sufficiently large $\overline{s}$, this effect is dominated by the effect on expected second-period payoffs.

[4] The result also holds if dispersion is measured by variance and/or if performance is measured by entrepreneur payoff.

[5] Finally, it is easy to characterize how μ^* varies with γ. It is immediate that u_L is increasing in γ: if successful outcomes are more heavily weighted, then pooling with the high type is more attractive. Hence, μ^* is decreasing in γ. For a stark illustration: in the limit where the reputational cost of unsuccessful outcomes is trivial compared to the benefit of successful ones (i.e., $\gamma \to \infty$), there is only upside to selecting eponymy and $\mu^* \to 0$.

Adding Entrepreneurial Effort

Introduce now that the likelihood of successful outcomes depends not only on the entrepreneur's type, but also on her *effort*. Specifically, after selecting s, the sender chooses effort level e from $[0,1]$, which is unobservable to the market, and incurs a cost of $c(e|\theta)$, which satisfies $c(0|\theta) = 0$, and for all $e > 0$, $c'(e|\theta) > 0$ and $c(e|L) \geq c(e|H)$. Finally, let $\pi(e|\theta) \equiv \Pr(g = h|e, \theta)$, which satisfies $\pi'(e|\theta) \geq 0$ and $\pi(e|H) \geq \pi(e|L)$ for all e.[6]

Recall that after the sender's selection of s, receivers update their beliefs to some μ_1. Having effort in the model means that the continuation game from this point is a "noisy" signaling game (as in Matthews and Mirman 1983; Carlsson and Dasgupta 1997), which we refer to as the "noisy signaling game endowed by (s, μ_1)." This is simply the game in which the receivers' prior over θ is μ_1, the sender chooses (unobservable) effort e, which leads to the distribution of g characterized by $\pi(e|\theta)$, and the sender's payoff is $U(s, \mu_1, \mu_2) - c(e|\theta)$. By definition of PBE, in any equilibrium of the model with effort, for all s (both on and off equilibrium path) continuation play corresponds to a PBE of the noisy signaling game endowed by $(s, \mu_1(s))$.

The procedure for finding equilibria is therefore to identify equilibrium effort levels for both types, $e^*_\theta(s, \mu_1)$ for every (s, μ_1)-pair. Then define $Q_\theta(s, \mu_1) = u_\theta(s, \mu_1) - c(e^*_\theta(s, \mu_1)|\theta)$. That is, $Q_\theta(s, \mu_1)$ is the sender's expected payoff given his choice of s, the first-period belief μ_1, and that play is according to the equilibrium in the endowed noisy signaling game—i.e., it accounts for both the sender's cost of effort and for the receivers' beliefs about the informativeness of first-period outcomes given the equilibrium effort levels. Q_θ is therefore the generalization of u_θ. The final step is to identify stable equilibria of the initial signaling stage in which s is chosen, using indifference curves corresponding to the level curves of Q_θ.[7]

Solving for equilibria explicitly is, in general, not tractable. We investigate via two examples.

Example 1. As in Tadelis (2002), $\pi(e|H) = p \in (0, 1)$ and $\pi(e|L) = e \cdot p$, and $c(e|L)$ is convex. For the convenience of interior solutions, let $c'(0|L) = 0$. To find the equilibrium of the effort stage, let $\tilde{e}$ be the level of effort that receivers anticipate from the low type. Therefore,

$$\mu_2(\mu_1, h|\tilde{e}) = \frac{\mu_1 p}{\mu_1 p + (1-\mu_1)\tilde{e}p}, \quad \text{and} \quad \mu_2(\mu_1, l|\tilde{e}) = \frac{\mu_1(1-p)}{\mu_1(1-p) + (1-\mu_1)(1-\tilde{e}p)}.$$

The low type seeks to solve:

$$\max_e \; epU(s, \mu_1, \mu_2(\mu_1, h|\tilde{e})) + (1-ep)U(s, \mu_1, \mu_2(\mu_1, l|\tilde{e})) - c(e|L).$$

[6]This setup strictly nests our original model in which, for all e, $\pi(e|H) = p$ and $\pi(e|L) = 1-p$. Because effort does not alter the probability of a successful outcome, both types select $e = 0$, and all of our preceding analysis applies.

[7]Technically, D1 and other stability-based refinements are not defined for games in which the sender undertakes a hidden effort choice. However, for any given model with hidden effort generating expected continuation payoff functions Q_H, Q_L, one can construct a signaling game that generates Q_θ as the sender's final payoff. By construction, there is a one-to-one correspondence between equilibria in the two games, and D1 is well defined for the second.

This problem is concave in e, so the solution is characterized by the first-order condition:

$$p\big(U(s,\mu_1,\mu_2(\mu_1,h|\tilde{e}))-U(s,\mu_1,\mu_2(\mu_1,l|\tilde{e}))\big)=c'(e|L).$$

Finally, in equilibrium $\tilde{e}=e$. Hence, the equilibrium of the effort stage is characterized by:

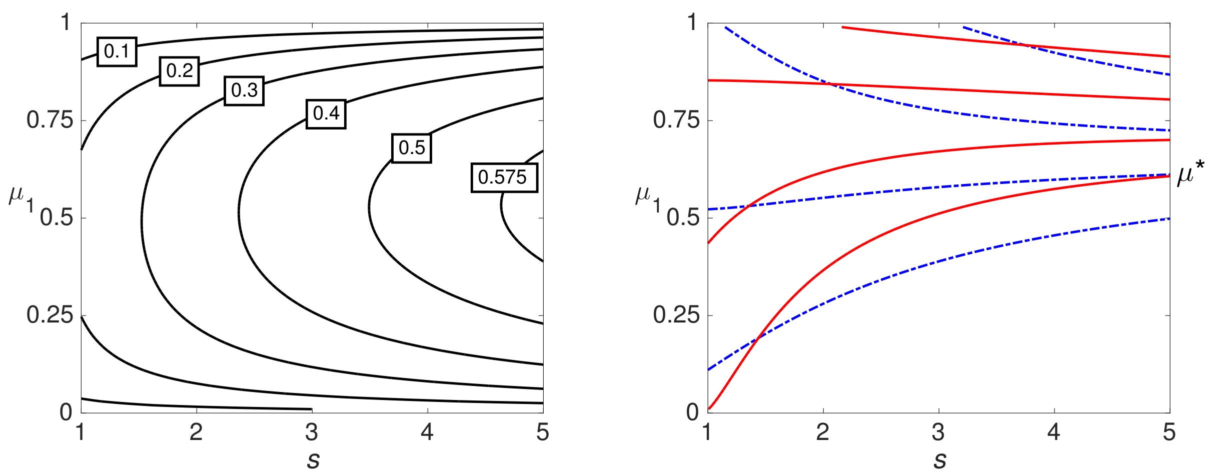
$$p\big(U(s,\mu_1,\mu_2(\mu_1,h|e))-U(s,\mu_1,\mu_2(\mu_1,l|e))\big)=c'(e|L). \tag{1}$$

For each (s,μ_1)-pair, (1) has a unique solution, $e^*_L(s,\mu_1)$. To see this, let $Z(e)$ denote the LHS of (1), and observe that:

$$\begin{aligned} &Z(0)=\frac{(1+\gamma)ps(1-\mu_1)}{1-p\mu_1}>0, && Z(1)=0, && \text{and } Z'(e)<0 \ \ \forall e.^{8} \\ &c'(0|L)=0, && c'(1|L)>0, && \text{and } c''(e|L)>0 \ \ \forall e. \end{aligned}$$

We can also note that Z is (linearly) increasing in s. It follows then that e^*_L is increasing in s; that is, (all else—in particular, μ_1—held equal) a greater chosen level of association between the firm and the entrepreneur amplifies the stakes, incentivizing greater entrepreneurial effort.

The next step is to use these equilibrium effort levels to construct Q_H, Q_L for each (s,μ_1) and analyze the initial signaling stage. Figure A2 illustrates a particular parametric example. Panel (a) shows a contour plot of the equilibrium effort levels. Panel (b) shows the high and low types' indifference curves. Note how the indifference curves maintain the essential structure of the original model (single-crossing, unique $\mu^*\in(0,1)$ such that $Q_L(\underline{s},0)=Q_L(\overline{s},\mu^*)$, etc.). Hence, Proposition 1 remains valid in this example.



(a) Effort Levels (b) Indifference Curves

Figure A2: Plots of effort levels and $Q_\theta(s,\mu_1)$-indifference curves (low type in solid red, high type in dashed blue) in Example 1 using $p=\frac{3}{4}$, $\gamma=\frac{1}{2}$, $\underline{s}=1$, $\overline{s}=5$, and $c(e|L)=2e^2$.

[8] $Z'(e)=-\frac{(1+\gamma)ps\mu_1(1-\mu_1)(1-p(e+\mu_1-e\mu_1)(e\mu_1-e-\mu_1+2))}{(e+\mu_1-e\mu_1)^2(ep(\mu_1-1)-p\mu_1+1)^2}<0.$

We previously observed that effort is increasing in s, all else equal. However, by Proposition 1, we know that, in equilibrium, $\mu_1(\underline{s}) = 0$ and $\mu_1(\overline{s}) = \mu^* > 0$; so all else is *not* held equal for different levels of s in equilibrium. Note that in Figure A2(a), for fixed μ_1, effort is increasing in s (as discussed); but also that for fixed s, effort is single-peaked in μ_1. The sender's only benefit from effort is influencing the market's belief that $\theta = H$, and the incentive to do so is highest when the market is most uncertain about θ. In particular, $e^*_L(\underline{s}, 0) = 0$ (if the market is already sure the sender is low type, there is no benefit to exerting effort), whereas $e^*_L(\overline{s}, \mu^*)$ is near the highest effort levels for among all (s, μ_1) pairs. Intuitively, entrepreneurs that select $s = \overline{s}$ (e.g., eponymy) exert more effort not only because the stakes are higher, but also because there is uncertainty about their type (i.e., $\mu^* \in (0, 1)$ since the equilibrium is partial pooling on $\overline{s}$).

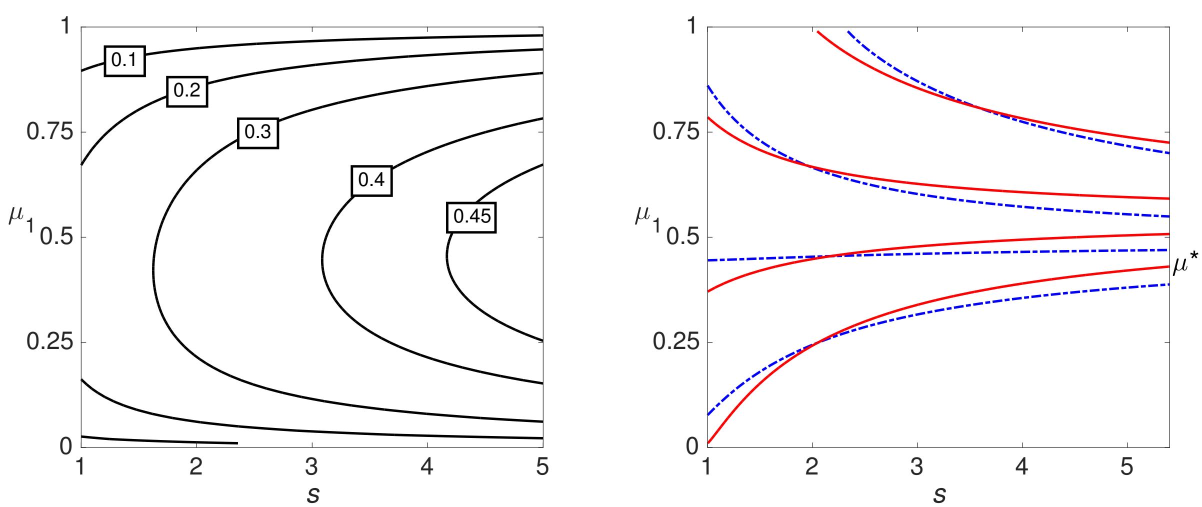
Example 2. In the previous example, only the low type exerts effort. To see that this feature is not critical, consider the following:

$$\pi(e|L) = \frac{e}{2}, \qquad \pi(e|H) = \frac{e}{2} + \frac{1}{4}, \qquad c(e|L) = c(e|H) = c(e) \equiv \frac{e^2}{2(1-e)}.$$

Going through the same steps as for Example 1, we see that the first-order condition is the same for both types:

$$\frac{1}{2}\big(U(s, \mu_1, \mu_2(\mu_1, h|\tilde{e})) - U(s, \mu_1, \mu_2(\mu_1, l|\tilde{e}))\big) = c'(e).$$

Hence, both types will exert the same effort for each (s, μ_1)-pair. Figure A3 shows a particular parametric example. The characterization of effort is similar to that in Figure A2, and the indifference curves again maintain their key features, so Proposition 1 remains valid.



(a) Effort Levels (b) Indifference Curves

Figure A3: Plots of effort levels and $Q_\theta(s, \mu_1)$-indifference curves (low type in solid red, high type in dashed blue) in Example 2 using $\gamma = 1$, $\underline{s} = 1$, $\overline{s} = 5$.

§B Identifying Eponymous Firms

The Eponymy Matching Process

Our dataset contains information from the Bureau van Dijk database that consists of over 44 million company-year observations, each with ownership information, for years 2002–2012. We included only shareholder records that are labeled as "individual" under the Shareholder Type field. We use Shareholder Name (SHN) and Company Name (COMP) to create our eponymy measure. Importantly, our data contains time-series information on shareholder and company names.

The eponymy matching process was implemented in STATA version 14. As of version 14, STATA does not work properly with files that contain extended ASCII characters (e.g., Ù, Ë, Ä, Æ), which are common in European company names and shareholder names. Consequently, all files were converted to Unicode UTF-8 encoding using STATA's `unicode translate` command in order for them to work properly with STATA 14. After translating the files, ligatures and letters that contained diacritics were replaced by their Latin character combination equivalent, (e.g., "Æ" with "AE," "ß" with "SS," and "Ü" with "UE"). Furthermore, STATA's string functions were used in their Unicode-aware version, for example, `ustrlen(var)` instead of `length(var)` function.

First, SHN and COMP variables were standardized by cleaning all non-alphabetic characters and converting all strings to uppercase characters. Next, the SHN variable was cleaned to distinguish between individual shareholders and legal-entity shareholders (which were sometimes incorrectly included under the individual shareholder). For this process, we formed a list of over 1,000 business-related terms and legal-entity endings (e.g., PLC, LLC, GMBH, SAS) commonly used in the countries in our sample. This list was compiled by manually checking the most frequent terms in the SHN field for non-name words (accordingly, the list is targeted to our sample). Some of these terms are prefixes or suffixes; for example, the suffix "-schaft" can match various German business words. All SHNs that were matched with the list were dropped from the dataset. The remaining observations were then further cleaned by removing preceding titles, such as "MR," "DR," "JR," "MADAME," and "MME" as well as other common words (e.g., "family," "children," "members," "and others"). After this process, 42 million company-year observations remained.

We were then able to use an automated string-matching algorithm on the standardized names to link the last name of a shareholder to the name of the firm. However, for accuracy purposes, names with less than three letters were excluded from the match. Using this process, and after extensive manual checks, we were able to match over 11 million individual shareholder records across the sample years. For our main analysis, only an exact match between the last name of the majority shareholder (i.e., holder of at least 50% of the firm's equity stakes) and a word in the firm name is classified as an eponymy match. We created a dummy for eponymy that receives the value of 1 for firms whose names include the name of the majority shareholder, and 0 for all other firms. There were 1,171,106 eponymy records, or 18.9% of firm-year observations in the final estimation sample used in our main analysis. The next subsection demonstrates the robustness of our results to alternative methods for classifying eponymy.

Alternative Matching

In our main analysis, we code a firm as eponymous if there is an exact match between the name of the firm and the name of the majority owner. Table A3 shows that our results are robust to relaxing both the exact-match and majority-owner requirements.

Column 1 shows that the eponymy-performance relationship is robust to coding eponymy based on an (exact) match between the name of the firm and the name of its leading shareholder, and the coefficient on eponymy is slightly lower than in the baseline specification. Column 2 includes an interaction between eponymy and a dummy for the firm having a majority owner, while Column 3 includes an interaction between eponymy and the amount of equity held by the leading shareholder. In both columns we see that the coefficient estimates of eponymy are higher when the leading shareholder (whose name is on the firm) holds a majority/larger stake in the company.

Columns 4 and 5 restrict the samples only to firms that have majority shareholders or are owned wholly by a single individual, respectively. Again our results are robust, and we see that the coefficient on eponymy is higher in Column 4 than in the baseline specification, and higher still when we look only at single-owner firms.

In addition to the exact-matching process described above, using STATA's `strdist` command, we calculated the distance between the leading owner's surname and each of the strings contained in the firm's name. The `strdist` command is based on the Levenshtein-distance metric, which measures the distance between two strings by the minimum number of character edits required to gain an exact match, normalized by string lengths. We used the closest distance score between the surname and the various strings of the firm's name as an alternative continuous measure of eponymy. By construction, the distance score is zero for eponymous firms. This match takes into account similar names, embedded names, spelling and other errors. For example, using this process we can match an owner last name "ROBENSON" with a company named "ROBINSON CO," as well as an owner named "NICHOLAS EVEREST" to a company name "NEVEREST," and an owner named "IAN TAYLOR" to a company listed as "TAYLORED COMMUNICATIONS."

Column 6 presents the estimation results using the Levenshtein-distance scores by quartiles. From Column 1, 22.4% of firms have an exact match between the firm name and the name of the leading shareholder. These firms, therefore, have Levenshtein-distance scores of zero and make up almost the entire first quartile of firms based on Levenshtein-distance scores. Reinforcing our results, see that the coefficient estimate on the first-quartile dummy is nearly identical to the estimated coefficient on eponymy in Column 1, and that the estimated coefficients on the remaining quartile-dummies are very close to zero.

Name Changes

The time-series dimension of our data allows us to analyze firm-name changes over time. To analyze name changes, we implemented an indirect matching based on the Levenshtein-distance algorithm that groups similar strings together. For each firm in our sample, the automated algorithm measures the distance between its company names across years (normalized by name lengths). It then matches a string pair if the normalized distance is above the 90th percentile value of the Levenshtein score (manual checking of matched results indicated this as the optimal threshold) and assigns to each group of matches a unique identification number. By construction, a firm that has more than one identification number attached to it has changed its name. This match takes into account similar names, spacing differences, spelling mistakes, and other data-entry errors. Before performing the match, company names were standardized and cleaned, converting all strings to uppercase characters and removing legal-entity endings and other common words such as "COMPANY," "GROUP," and "INTERNATIONAL." This further enabled us to match cases such as "JOHNS INTERNATIONAL" and "JOHNS CO," for which direct matching would classify incorrectly as a name change.

A total of 42,510 (out of the 1.8 million) firms changed their names during our sample period. As presented in Table A6, the majority of name changes are by non-eponymous firms that remain non-eponymous (39,076 firms). A total of 2,205 eponymous firms changed their names to become non-eponymous. Finally, 1,229 non-eponymous firms changed their names to become eponymous. Table A4 presents descriptive statistics on firms that changed their name versus firms that kept the same name throughout the complete sample period.

Table A5 presents econometric evidence for the relationship between performance and name changes. We find a negative relationship between past performance and the probability of a name change (Column 1). Based on the estimates from Column 1, a two-standard-deviation increase in lagged ROA reduced the likelihood of a name change by 0.3 of a percentage point. Moreover, eponymous firms are less likely to change their name, especially when performing well (Column 2). Columns 3-5 distinguish between three types of name changes: (*i*) non-eponymous becoming eponymous, (*ii*) eponymous becoming non-eponymous, and (*iii*) non-eponymous changing to another non-eponymous name. Column 3 shows that there is no statistically significant relationship between past performance and name changes for non-eponymous firms that become eponymous (only 1,229 firms fall into this category). Yet, Column 4 shows that there is a negative relationship between performance and name changes for eponymous firms that become non-eponymous (i.e., among eponymous firms, poor performance is correlated with changing to a non-eponymous name). However, these estimates are on a small set of eponymous firms that become non-eponymous by changing their name (2,205 firms fall into this category). Finally, Column 5 documents a negative relationship between past performance and name changes for non-eponymous firms that remain non-eponymous after the name change (39,076 non-eponymous firms change their name and remain non-eponymous).

In summary, the analysis of the relationship between past performance and names changes suggests a pattern where name changes are very rare, but when they do occur, they follow years with bad financial performance (consistent with Tadelis (1999, 2002) and McDevitt (2011)). Nevertheless, to ensure that changes in eponymy status are not driving our findings, Column 7 of Table A3 shows that our estimation results are robust when the sample is restricted to only firms that have no change in eponymy status during the sample period.[9]

[9]Note that eponymy status can change due to either a change in the firm name or a change in ownership. However, ownership changes that alter eponymy status are even rarer than name changes that alter eponymy status (see Table A6).

§C Additional Empirical Results and Robustness

Evidence from Dun and Bradstreet

We also test our predictions using a large dataset of American firms. We utilize Dun and Bradstreet (D&B) data on credit ratings and financial risk for 60,853 American firms. The D&B ratings provide composite appraisals of firm creditworthiness based on their financial accounts, payment history, and third-party evaluations of risk ratings. Firms are ranked along these measures to allow for direct comparisons.

For each firm, we also observe the individual listed as the key contact person. Our conversations with D&B indicate that this individual is typically the owner or CEO. Note that for the D&B sample of firms, we do not have the rich information on ownership as in Amadeus. Moreover, the data are cross-sectional, and thus we cannot perform the same detailed analysis on ownership changes and within-firm variation in eponymy as we did for the main sample. The D&B data do provide the advantage of having several measures of performance related to creditworthiness that are especially important for small firms. In addition, the dataset allows us to corroborate our earlier results with a completely different dataset with firms located in a different part of the world.

With these considerations in mind, we follow a procedure analogous to that employed in the Amadeus sample to determine eponymy by comparing the name of the firm to the last name of the main contact person. We find 12.5% of firms in the D&B sample are eponymously named. We proceed to examine the relationship between eponymy and a wide set of financial-strength indicators provided by D&B. After several correspondences with D&B, we have confirmed that in computing their scores, they do not take eponymy into consideration, nor any other similar measure of owner skills. Table A8 presents the estimation results for the relationships between eponymy and D&B financial indicators.

We begin by examining the relationship between eponymy and credit score. A firm's credit-score percentile is an outcome variable that ranges from 1 to 100, where 1 is assigned to firms with the highest probability of severe delinquency in paying its bills and 100 represents firms with the lowest risk of delinquency, based on an overall assessment of each firm's creditworthiness or ability to take on additional debt. Based on the credit-score distribution, we generate a dummy variable that receives the value of 1 for firms in the highest-score quartile, and use this variable as our dependent variable. Column 1 presents the estimation results of a Probit model for the relationship between the high-credit-score dummy and eponymy. We find a positive and significant relationship between eponymy and credit score.

In Column 2, we examine the relationship between eponymy and financial stress. The financial-stress score is an indicator of the business's likelihood of failure compared to the national average and the focal industry. The score is based on a multitude of demographic and financial information, credit history, and public filings. The variable takes the value of 1 if a firm has the highest probability of financial stress, and the value of 100 if a firm has the lowest risk of business failure. We construct a dummy variable that equals 1 if the score falls into the fourth quartile of the score distribution. We estimate a Probit model using this indicator as the dependent variable. The coefficient estimate on the eponymy dummy is also positive and significant, implying a lower risk of financial stress and failure for eponymous firms.

Next, we examine the likelihood of supplier failure for eponymous firms. The Supplier Evaluation Risk Rating (SIR) ranks firms according to their probability of obtaining legal relief from creditors or ceasing operations without paying their creditors in full in the next 12 months. The rating ranges from 1 to 9, with 1 representing firms that have the lowest probability of supplier failure, and 9 for firms with the highest probability of supplier failure. Our dependent variable is a dummy variable that receives the value of 1 for firms with very low supplier risk—an SIR score of 1 or 2. This score indicates a failure risk of less than 0.16% (6% of the population of firms has such low risk). Our results are robust to alternative risk cutoffs. The estimated coefficient is positive and significant for eponymous firms, again indicating a lower risk of failure (Column 3).

In Columns 4 and 5, we use records on the timeliness of payments by the firm as outcome variables. First, we explore how the probability of on-time payment varies with eponymy. We construct a dummy variable for on-time payment that equals 1 if a firm has been prompt in making its payments to creditors—their D&B Paydex score is 80 and above (the range is from 20 to 100, with scores above 80 indicating prompt payments). Column 4 reports a positive and significant estimate on the eponymy dummy. In Column 5, we use a count of past-due and delinquent payments in the past 12 months for each firm as a measure of slow payments or non-payments. We estimate this specification using a Negative Binomial count model. The estimated coefficient on the eponymy dummy is negative and significant, which is consistent with the overall pattern of greater financial performance of eponymous firms.

Next, we employ two additional tests by utilizing data on legal and collection recourse actions initiated against firms. In Column 6, we estimate a negative binomial model for the number of liens for each company as a measure of the potential impact of legal action on a company's financial stability. The number-of-liens variable counts the number of claims against firm property held by creditors as security for the satisfaction of debt. The coefficient estimate on the eponymy dummy is negative and significant and thus indicates fewer liens held for eponymous firms than for non-eponymous firms. In Column 7, we use a dummy for a collections indicator, which equals 1 if a firm has been sent a collections notice on an unpaid obligation (which happens for about 5% of our firm sample). The estimated coefficient on the eponymy dummy is negative and significant, as expected. Overall, the results from the D&B sample of firms provide additional, independent confirmation of our main findings on eponymy and its relationship to financial performance.

Industry Variation and Hypothesis 3

Returning to our main sample, the data allows us to investigate whether, and how, the relationship between firm performance and eponymy varies, depending on industry characteristics (see Table A1 for the industries represented in our data). We find that the relationship is stronger for *i*) industries with greater performance dispersion; *ii*) service industries (compared to manufacturing); and *iii*) industries we characterized as less "routine."

In light of Hypothesis 3, one explanation of these empirical results is that market information about firm quality (i.e., the realization of g) more accurately reflects the entrepreneur's ability in industries with these characteristics. Regarding (i), this merely gives an intuitive explanation for the covariance in performance dispersion and the strength of the eponymy-performance relationship: if the market has relatively accurate information in an industry, this leads to both greater performance dispersion and a stronger link between eponymy and performance. Regarding (ii) and (iii), we find the assumption plausible; in service or less routinized industries, there is arguably a more direct connection between the skills of the purveyor (who is often the entrepreneur herself given that most of the firms in the dataset are small) and the realized product. Of course, this assumption need not be universally true, but must only hold in aggregate to explain the data.

Table A9 shows the relationship between eponymy and ROA by industry characteristics in our data.

Performance Dispersion. We follow Acemoglu et al. (2007) and measure an industry's dispersion of performance as the difference between the highest and lowest performing firms. We use the complete Amadeus database over the years 2002-2012 to compute the difference between the 95th and 5th percentiles of ROA. Column 1 presents the estimation results for industry performance dispersion. Consistent with our prediction, the coefficient estimate on the interaction between industry dispersion and eponymy is positive and highly significant. Relative to the average industry dispersion value, a one-standard deviation increase in this value raises the estimated coefficient on eponymy from 0.032 to 0.05.

Services vs. Manufacturing. We manually classify industries into services or manufacturing based on their SIC code description. Column 2 includes an interaction between a dummy variable that receives the value of 1 for manufacturing and 0 for services. The coefficient estimate on this interaction is negative, highly significant, and very large, indicating the eponymy-performance relationship is stronger in service industries.

Routineness. Column 3 adds an interaction between eponymy and one measure of the level of "routineness" in the industry.[10] The results are consistent with our theory. The eponymy-performance relationship decreases in the industry's level of routineness. Relative to the average value, a one-standard-deviation decrease in industry routineness raises the estimated coefficient on eponymy from 0.033 to 0.068. For robustness, we include measures of how the eponymy-performance relationship varies with Tobins Q and R&D intensity. Like routineness, these measures also capture features of industries in which "intangibles" play a greater role, which may be related to a greater importance of owner skills. Columns 4 and 5 are consistent with our predictions. Relative to the average Tobin's Q value, a one-standard deviation increase in the industry measure raises the coefficient estimate on eponymy from 0.025 to 0.053 (Column 4). For R&D intensity, as expected, the coefficient estimate on this interaction is positive and highly significant. Relative to the average industry R&D intensity value, a one-standard deviation increase in this value doubles the coefficient estimate on eponymy (from 0.037 to 0.08) (Column 5).

[10] We follow Costinot, Oldenski, and Rauch (2011) and rank industries according to their level of task "routineness," using data from the U.S. Department of Labor's Occupational Information Network (O*NET) and measuring the level of task routineness by the extent to which the task involves "making decisions and solving problems."

Eponymy and Effort

Section 4 of the main text observed that effort could potentially play a role in the eponymy-performance relationship, and §A of this appendix explored this possibility by extending our model.

To empirically investigate the possibility that eponymous entrepreneurs exert greater effort, we matched the firms in our data to the World Management Survey (Bloom and Van Reenen, 2007), which also samples firms from the Amadeus database and includes detailed information on management practices. For this match, we classified firms as eponymous if any shareholder (not just the majority shareholder) had a surname that was identical to the name of the firm. We used this approach because the World Management Survey does not have detailed ownership data for all shareholders in every instance. In those cases where there was no ownership data, we manually examined firm websites to classify them as eponymous or not. In sum, for this robustness check, our sample consists of 1,977 European firms that participated in the World Management Survey, and we classify 432 of them as eponymous. Note the number of observations in each column of Table A10 does not total 1,977 because we do not have information on all variables for the entire sample.

Using several different dependent variables, we do not find evidence that eponymous firms are being managed differently than non-eponymous firms. Of particular relevance to the effort mechanism, we find no statistically significant differences in hours worked (Columns 2-4) or days taken off (Columns 5-6) between eponymous and non-eponymous firms (i.e., the coefficient on the eponymy indicator is not statistically significant).[11] Nor does it appear that eponymous owners are disproportionately using high-powered incentives and monitoring to motivate their employees to exert more effort (Columns 7-9). While effort exerted is difficult to observe and measure, this initial analysis does not appear to support the idea that greater effort is driving superior performance among eponymous entrepreneurs.

References

[1] Acemoglu, D., P. Aghion, C. Lelarge, J. Van Reenen, and F. Zilibotti (2007). "Technology, information, and the decentralization of the firm." *Quarterly Journal of Economics* 122(4): 1759–99.

[2] Banks, J. and J. Sobel (1987). "Equilibrium selection in signaling games." *Econometrica* 55: 647–662.

[3] Bloom, N. and J. Van Reenen (2007). "Measuring and explaining management practices across firms and countries." *Quarterly Journal of Economics* 122:4, 1351–1408.

[4] Carlsson, H. and S. Dasgupta (1997). "Noise-proof equilibria in two-action signaling games." *Journal of Economic Theory* 77: 432–460.

[5] Cho, I. K. and D. Kreps (1987). "Signaling games and stable equilibria." *Quarterly Journal of Economics* 102: 179–221.

[11] Though, with a relatively small number of observations in Columns 5-6.

[6] Costinot, A., L. Oldenski, and J. Rauch (2011). "Adaptation and the boundary of multinational firms." *Review of Economics and Statistics* 93:1, 298–308.

[7] Daley, B. and B. Green (2014). "Market signaling with grades." *Journal of Economic Theory* 151(1): 114–145.

[8] Matthews, S. A. and L. J. Mirman (1983), "Equilibrium limit pricing: The effects of private information and stochastic demand." *Econometrica* 51: 981–996.

[9] McDevitt, R. (2011). "Names and reputations: An empirical analysis." *American Economic Journal: Microeconomics* 3(3): 193–209.

[10] Tadelis, S. (1999). "What's in a name? Reputation as a tradable asset." *American Economic Review* 89(3): 548–63.

[11] Tadelis, S. (2002). "The market for reputations as an incentive mechanism." *Journal of Political Economy* 110(4): 854–82.

Table A1. Eponymy Incidence by Main Industries

2-digit SIC code	Industry	Firms	Observations	Eponymous	% eponymous
01	Agricultural Production - Crops	9,330	29,995	5,419	18.1
02	Agricultural Production - Livestock and Animal Specialties	7,237	27,525	4,232	15.4
07	Agricultural Services	8,467	28,764	7,858	27.3
08	Forestry	1,346	4,886	1,186	24.3
09	Fishing, Hunting and Trapping	1,880	8,992	1,180	13.1
10	Metal Mining	246	907	74	8.2
12	Coal Mining	113	406	51	12.6
13	Oil and Gas Extraction	859	3,114	360	11.6
14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels	3,675	14,154	2,728	19.3
15	Building Cnstrctn - General Contractors & Operative Builders	129,842	387,049	92,725	24.0
16	Heavy Cnstrctn, Except Building Construction - Contractors	13,546	47,956	13,542	28.2
17	Construction - Special Trade Contractors	143,522	510,467	171,419	33.6
20	Food and Kindred Products	26,523	102,056	21,656	21.2
21	Tobacco Products	141	467	67	14.3
22	Textile Mill Products	9,297	35,329	6,083	17.2
23	Apparel, Finished Prdcts from Fabrics & Similar Materials	12,290	43,160	7,594	17.6
24	Lumber and Wood Products, Except Furniture	15,124	59,477	18,059	30.4
25	Furniture and Fixtures	10,897	39,153	9,713	24.8
26	Paper and Allied Products	5,297	20,636	2,402	11.6
27	Printing, Publishing and Allied Industries	25,087	93,628	10,580	11.3
28	Chemicals and Allied Products	7,502	29,094	2,287	7.9
29	Petroleum Refining and Related Industries	312	933	43	4.6
30	Rubber and Miscellaneous Plastic Products	9,604	36,120	4,043	11.2
31	Leather and Leather Products	6,438	22,506	4,584	20.4
32	Stone, Clay, Glass, and Concrete Products	13,631	50,237	10,063	20.0
33	Primary Metal Industries	7,162	26,465	3,580	13.5
34	Fabricated Metal Prdcts, Except Machinery & Transport Eqpmnt	46,344	164,861	35,122	21.3
35	Industrial and Commercial Machinery and Computer Equipment	26,839	89,783	13,667	15.2
36	Electronic, Elctrcl Eqpmnt & Cmpnts, Excpt Computer Eqpmnt	11,749	39,372	3,384	8.6
37	Transportation Equipment	6,413	22,614	3,862	17.1
38	Mesr/Anlyz/Cntrl Instrmnts; Photo/Med/Opt Gds; Watchs/Clocks	5,987	19,268	2,590	13.4
39	Miscellaneous Manufacturing Industries	6,977	23,595	4,076	17.3
40	Railroad Transportation	283	684	91	13.3
41	Local, Suburban Transit & Interurbn Hgwy Passenger Transport	11,349	41,005	9,451	23.0
42	Motor Freight Transportation	36,781	132,103	46,508	35.2
43	United States Postal Service	935	2,895	305	10.5
44	Water Transportation	3,815	14,497	1,713	11.8
45	Transportation by Air	1,230	3,992	334	8.4
46	Pipelines, Except Natural Gas	27	89	10	11.2
47	Transportation Services	18,606	60,975	7,080	11.6
48	Communications	5,661	17,668	1,180	6.7
49	Electric, Gas and Sanitary Services	9,535	28,377	4,092	14.4
50	Wholesale Trade - Durable Goods	146,062	544,729	92,967	17.1
51	Wholesale Trade - Nondurable Goods	86,916	326,848	62,983	19.3
52	Building Matrials, Hrdwr, Garden Supply & Mobile Home Dealrs	14,943	56,504	14,139	25.0
53	General Merchandise Stores	6,416	22,247	3,298	14.8
54	Food Stores	28,339	100,727	24,342	24.2
55	Automotive Dealers and Gasoline Service Stations	12,409	46,455	11,718	25.2
56	Apparel and Accessory Stores	34,193	121,594	23,104	19.0
57	Home Furniture, Furnishings and Equipment Stores	30,241	116,581	23,773	20.4
58	Eating and Drinking Places	62,959	185,459	25,588	13.8
59	Miscellaneous Retail	59,674	205,740	41,497	20.2
60	Depository Institutions	4,128	9,927	992	10.0
61	Nondepository Credit Institutions	13,298	48,569	6,698	13.8
62	Security & Commodity Brokers, Dealers, Exchanges & Services	1,143	4,049	423	10.4
63	Insurance Carriers	2,701	9,156	1,991	21.7
64	Insurance Agents, Brokers and Service	7,543	21,485	5,327	24.8
65	Real Estate	177,215	571,724	64,211	11.2
67	Holding and Other Investment Offices	23,838	69,775	11,866	17.0
70	Hotels, Rooming Houses, Camps, and Other Lodging Places	20,672	62,362	5,083	8.2
72	Personal Services	29,693	100,487	17,577	17.5
73	Business Services	166,927	516,055	53,131	10.3
75	Automotive Repair, Services and Parking	27,395	97,216	26,650	27.4
76	Miscellaneous Repair Services	9,566	36,296	7,595	20.9
78	Motion Pictures	6,407	19,306	1,232	6.4
79	Amusement and Recreation Services	24,078	73,484	7,530	10.2
80	Health Services	28,427	92,218	24,313	26.4
81	Legal Services	4,781	14,552	6,915	47.5
82	Educational Services	14,217	45,019	4,707	10.5
83	Social Services	4,664	14,447	1,091	7.6
84	Museums, Art Galleries and Botanical and Zoological Gardens	358	1,222	70	5.7
86	Membership Organizations	492	1,615	180	11.1
87	Engineering, Accounting, Research, Management & Related Svcs	110,190	365,009	63,989	17.5
89	Services, Not Elsewhere Classified	4	22	2	9.1
91	Executive, Legislative & General Government, Except Finance	505	1,623	175	10.8
92	Justice, Public Order and Safety	432	1,442	124	8.6
94	Administration of Human Resource Programs	76	253	18	7.1
95	Administration of Environmental Quality and Housing Programs	166	532	97	18.2
96	Administration of Economic Programs	38	100	3	3.0
97	National Security and International Affairs	671	1,211	122	10.1
Others	Others	654	2,468	592	24.0
Total		1,824,330	6,193,762	1,171,106	18.9

Table A2. The Relationship Between Eponymy, Firm Age and ROA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: *Return on Assets* (*Profits/Assets*)								
Sample:	Firm age				Only surviving firms	Surviving firms inc. in 2003		
	1st quartile	2nd quartile	3rd quartile	4th quartile	Pooled	Pooled	Within-firms	Between-firms (2007)
Dummy for eponymous	0.071	0.023	0.008	0.001	0.009	0.034	0.023	0.034
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.012)	(0.008)
Dummy for eponymous × *Firm age*					-0.001	-0.001	-0.001	-0.001
					(0.001)	(0.000)	(0.001)	(0.000)
Firm age					-0.001	-0.001	-0.001	-0.001
					(0.001)	(0.000)	(0.001)	(0.000)
ln(*Assets*)	0.009	0.005	0.011	0.011	0.011	-0.009	0.086	-0.014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)	(0.002)
ln(*No. shareholders*)	-0.042	-0.022	-0.009	-0.004	-0.001	-0.022	0.000	-0.029
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Equity dispersion	-0.031	-0.008	-0.009	-0.007	-0.007	0.017	0.012	0.018
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.005)
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	-	Yes
Firm fixed-effects	-	-	-	-	-	-	Yes	-
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Average ROA sample value:	0.106	0.055	0.034	0.018	0.040	0.064	0.064	0.080
% eponymy:	0.170	0.184	0.193	0.207	0.199	0.190	0.190	0.191
Observations	1,603,874	1,182,098	1,309,399	1,247,012	455,464	341,532	341,532	36,264
R-squared	0.14	0.09	0.06	0.04	0.06	0.11	0.58	0.13

Note: This table examines how the relationship between eponymy and ROA varies with firm age. Column 1-4 show how the relationship between eponymy and ROA varies by quartile of firm age. Column 5 restrict the sample to any surviving firms during the complete sample period. Columns 6-8 includes only surviving firms incorporated at the beginning of our sample. Standard errors are clustered by firms. * and ** indicates statistical significance at the 5% and 1% level, respectively.

Table A3. Alternative Eponymy Classifications

	Dependent variable: *Return on Assets* (*Profits/Assets*)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Eponymy based on leading shareholder	Eponymy based on leading shareholder	Eponymy based on leading shareholder	Only majority shareholder firms	Single-owner firms	Levenshtein name matching (quartile)	No change in epo-status	Within-Firms (only name changes)	Within-Firms (only ownership changes)
Dummy for eponymous	0.027	0.024	0.017	0.034	0.051		0.031	0.010	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.003)	(0.003)
Dummy for majority shareholder× Dummy for Eponymous		0.004							
		(0.001)							
Dummy for majority shareholder		0.027							
		(0.001)							
Equity by leading shareholder × Dummy for Eponymous			0.017						
			(0.002)						
Equity by leading shareholder			0.048						
			(0.001)						
Dummy for name match distance:									
1st quintile - Eponymy						0.026			
						(0.001)			
2nd quintile						0.002			
						(0.001)			
3rd quintile						0.001			
						(0.001)			
4th quintile						Base			
ln(*Assets*)	0.009	0.008	0.010	0.010	0.012	0.011	0.011	0.124	0.124
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(*No. shareholders*)	-0.026			-0.026		-0.026	-0.025	-0.004	-0.004
	(0.001)			(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Equity dispersion	-0.019			-0.013		-0.023	-0.020	0.005	0.005
	(0.001)			(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Firm fixed-effects	No	No	No	No	No	No	No	Yes	Yes
Three-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-	-
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-	-
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average ROA sample value:	0.053	0.053	0.053	0.063	0.083	0.053	0.053	0.053	0.053
% Eponymy	0.224	0.224	0.224	0.269	0.273	0.189	0.182	0.188	0.188
Observations	6,193,762	6,193,762	6,193,762	2,840,870	1,382,040	6,193,762	6,166,387	6,179,832	6,168,218
Firms	1,824,330	1,824,330	1,824,330	960,376	483,246	1,824,330	1,818,855	1,822,274	1,820,881
R-squared	0.09	0.09	0.09	0.114	0.136	0.09	0.09	0.67	0.67

Notes: This table present OLS estimation results of the relationship between eponymy and ROA for alternative eponymy classifications. Column 1 classifies firms as eponymous if there is at least one leading shareholder with a last name that matches the firm's name, for any known equity stake value. Column 2 adds an interaction between eponymous and a dummy for whether the stakes of the leading shareholder are larger than 50%. Column 3 adds an interaction between eponymous and a continuous measure of share of equity held by the leading shareholder. Column 4 includes only firms with a majority shareholder (a shareholder with at least 50% of the firm's equity). Column 5 includes only firms where the leading shareholder owns 100% of the firm's equity. Columns 6 computes the number of character edits required to gain an exact match between owner name and the closest string in the firm name normalized by name lengths. The process compares both strings and assigns a matching score. By construction, this score is zero for eponymous firms. Column 6 allows for non-linear effects by including a complete set of quartile dummies. Standard errors (in parentheses) are robust to arbitrary heteroscedasticity and allow for serial correlation through clustering by firms. * and ** indicate statistical significance at the 5% and 1% level, respectively.

Table A4. Name Changing *vs.* Non-Name Changing Firms

		Name Change				Non-Name Change			
Variable	Name-change minus Non-Name-change	Obs.	Mean	Median	Std. Dev.	Obs.	Mean	Median	Std. Dev.
Returns on Assets	-0.02**	246,521	0.030	0.032	0.367	5,947,241	0.054	0.025	0.369
Sales ($,'000)	16,489**	246,521	24,830	617	659,488	5,947,241	8,341	436	322,426
Assets ($,'000)	24,196**	246,521	37,920	607	1,514,927	5,947,241	13,724	434	2,157,397
Number of employees	80**	149,362	130	6	2,071	3,600,117	49	5	1,529
Number of shareholders	0.1**	246,521	2.4	2	4	5,947,241	2.3	2	4

Notes: This table presents mean comparison tests for firms that changed their names at least once and firms that never changed their name in the 2002-2012 sample period. ** denotes that the difference in means is significant at the 1 percent level.

Table A5. Name Changes

	Dependent variable: *Dummy for a name change*				
	(1)	(2)	(3)	(4)	(5)
Sample	All firms	All firms	Name change into eponymous	Name change out of eponymous	Name change Non-Epo. to Non-Epo.
ROA_{t-1}	-0.004	-0.004	0.0001	-0.0001	-0.004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dummy for eponymous$_{t-1}$		-0.009			
		(0.000)			
Dummy for eponymous$_{t-1} \times ROA_{t-1}$		-0.002			
		(0.000)			
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Average sample value (×10):	0.1	0.1	0.003	0.005	0.09
Observations	4,369,432	4,369,432	4,173,420	4,179,384	4,347,470
Firms	1,372,493	1,372,493	1,331,212	1,332,188	1,369,059
R-squared	0.001	0.001	0.001	0.001	0.001

Notes: This table presents OLS estimation results for the relationship between name changes and firm performance. Average ROA_{t-1} is 0.06 (standard deviation of 0.35 and median of 0.03). Average sample values are multiplied by 10. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. * and ** indicate statistical significance at the 5% and 1% level, respectively.

Table A6. Name and ownership changes for eponymous and non-eponymous firms

	Name change	Ownership change	Total Status change
Eponymous to Non-eponymous	2,205	1,464	3,669
Non-eponymous to Eponymous	1,229	577	1,806
Non-eponymous to Non-eponymous	39,076	-	-
Total	42,510	2,041	5,475

Table A7. Examples of Name Change and Eponymy Reclassification

Direction	BVD	SIC	Previous Name	Year Change	Name change	Address	Shareholder
Non-eponymy to eponymy	DE2011194531	501	stop + go Auto Sofort Service Berlin-Treptow GmbH	2007	Zellmann Auto Sofort Service GmbH	Wegedornstraße 30, 12524 Berlin	ZELLMANN, BRIGITTE
Non-eponymy to eponymy	DE2011081923	736	Time Tec Berlin GmbH	2009	Rosinke Personalservice GmbH	Chausseestraße 92, Berlin, Berlin, Germany	ROSINKE, RAINER
Non-eponymy to eponymy	PT507481100	279	Print'n Go Lda	2010	Marques Associados Print Lda	E.N. 1 nº 4156 . Apartado/PO Box 59 3780-901 Avelãs de Caminho, Anadia Aveiro - Portugal	LUIS MANUEL ALMEIDA MARQUES
Eponymy to non-eponymy	NO986729631	565	Holmsen Clothing AS	2010	With Style since 1895 AS	Nordre Grenseveg 15, 2615 Lillehammer	HOLMSEN LASSE
Eponymy to non-eponymy	DE2190417671	596	HAAS MEDIA GMBH	2006	CONNOX GMBH	Warmbüchenstraße 21, 30159 Hannover, Germany	HAAS, THILO
Eponymy to non-eponymy	FR340360403	874	Serge MERLIN Conseil	2008	PIVADIS	24 Rue de la Bredauche, 45380 La Chapelle-Saint-Mesmin, France	M MERLIN SERGE
Non-eponymy to non-eponymy	AT9070034617	653	SPORT EYBL Immobilien AG	2008	Sport Service GmbH	Flugplatzstraße 30 4600 Wels	JANK, FRIEDRICH
Non-eponymy to non-eponymy	GB02952592	874	Acm (West) Limited	2005	Futur Limited	144 Manchester Road, Carrington Manchester, M31 4Qn	TIMOTHY P BOSTWICK
Non-eponymy to non-eponymy	NO983553184	504	Fagtorget AS	2006	M2 Capital AS	Nansetgata 102, 3269 Larvik	ERIKSEN PÅL

Table A8. Evidence from Dun and Bradstreet

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Dummy for high credit score	Dummy for low financial stress	Dummy for low supplier risk	Dummy for on-time payment	Number of past-due bills	Number of legal actions	Dummy for collection notice
Dummy for eponymous	0.012	0.025	0.007	0.015	-0.518	-0.213	-0.005
	(0.004)	(0.005)	(0.002)	(0.004)	(0.072)	(0.087)	(0.002)
ln(*Sales*)$_{t-1}$	0.008	0.008	0.011	-0.014	0.386	-0.010	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.017)	(0.010)	(0.001)
ln(*Firm age*)	0.059	0.110	0.041	-0.091	1.193	-0.033	0.005
	(0.001)	(0.002)	(0.001)	(0.003)	(0.036)	(0.029)	(0.001)
Three-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average sample value:	0.12	0.21	0.06	0.12	3.69	1.47	0.04
Firms	60,565	60,631	59,171	60,456	60,853	7,375	59,189
R-squared/Log likelihood	0.12	0.15	0.23	0.15	-117,897	-11,596	0.04

Notes: This table presents the estimation results of the relationship between eponymy and a set of financial risk and stability indicators from Dun and Bradstreet. The share of eponymous firms in this sample is 12.5% (as compared to 18.9% in the Amadeus sample). Columns 1-4 and 7 are estimated using a Probit model. Columns 5 and 6 present the estimation results of negative binomial count models. For the Probit and Negative Binomial specifications marginal effects are reported. All other specifications are estimated using OLS. The estimation is cross-sectional for 2012 American firms. Robust standard errors are in parentheses. * and ** indicate statistical significance at the 5% and 1% level, respectively.

Table A9. Variation by Industry Characteristics

Dependent variable: *Return on Assets* (*Profits/Assets*)					
	(1)	(2)	(3)	(4)	(5)
Dummy for eponymous	-0.006	0.035	0.316	-0.014	-0.020
	(0.001)	(0.001)	(0.009)	(0.002)	(0.001)
Dummy for eponymous × *Industry growth dispersion*	0.026				
	(0.001)				
Dummy for eponymous × *Dummy for Manufacturing*		-0.025			
		(0.001)			
Dummy for eponymous × *Industry routineness*			-0.742		
			(0.023)		
Dummy for eponymous × *Industry Tobin's Q*				0.018	
				(0.001)	
Dummy for eponymous × *Industry R&D intensity*					1.189
					(0.033)
ln(*Assets*)	0.011	0.011	0.009	0.008	0.009
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(*No. shareholders*)	-0.025	-0.025	-0.024	-0.023	-0.026
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Equity dispersion	-0.020	-0.020	-0.019	-0.027	-0.021
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Three-digit SIC dummies	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Average ROA sample value:	0.054	0.053	0.053	0.052	0.054
Industry measure average:	1.48	0.218	0.380	2.19	0.048
Industry measure std.:	0.665	0.413	0.047	1.52	0.036
% Eponymy	0.189	0.189	0.189	0.173	0.172
Observations	5,995,438	6,183,264	6,130,039	1,647,805	4,836,148
Firms	1,758,717	1,820,898	1,804,732	477,692	1,443,113
R-squared	0.09	0.09	0.09	0.10	0.10

Notes: This table presents OLS estimation results of how the relationship between eponymy and return on assets varies with industry characteristics. Standard errors (in parentheses) are robust to arbitrary heteroscedasticity and allow for serial correlation through clustering by firms. ** significant at 1%; * significant at 5%.

Table A10. World Management Survey

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable:	Dummy for Family	Avg. hours worked, all workers	Avg. hours worked, managers	Avg. hours worked, non-managers	Days holiday	Days sickleave	Bonus pay	Promotion	Monitoring	Avg. people management	Avg. management quality
Dummy for eponymous	0.264	-0.249	-0.748	-0.194	1.925	-0.118	-0.435	-0.792	-0.073	-0.003	-0.043
	(0.031)	(0.245)	(0.483)	(0.239)	(1.065)	(1.214)	(0.825)	(1.788)	(0.052)	(0.042)	(0.041)
ln(*Number of employees*)	-0.017	-0.017	0.702	0.015	0.152	0.359	1.500	-1.002	0.170	0.098	0.138
	(0.010)	(0.080)	(0.163)	(0.083)	(0.380)	(0.363)	(0.285)	(0.616)	(0.020)	(0.017)	(0.016)
ln(*Firm foundation year*)	-0.810	-1.487	-1.500	1.359	-25.516	20.270	-22.328	-38.035	0.264	0.137	0.205
	(0.501)	(4.040)	(8.310)	(4.070)	(19.072)	(15.450)	(15.642)	(34.757)	(0.855)	(0.711)	(0.677)
Dummy for family		0.272	0.043	0.451			0.526	0.517	-0.130	-0.062	-0.106
		(0.234)	(0.458)	(0.231)			(0.903)	(1.778)	(0.047)	(0.039)	(0.037)
Three-digit SIC dummies	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,496	1,397	1,449	1,463	118	101	1,388	714	1,496	1,496	1,496
R-squared	0.21	0.29	0.17	0.31	0.16	0.15	0.12	0.16	0.19	0.15	0.20

Notes: This table presents the relationship between measures of effort from the World Management Survey and eponymy. * and ** indicate statistical significance at the 5% and 1% level, respectively.

Figure A4. Cumulative Distribution of Firm Performance For Eponymous vs. Non-Eponymous Firms by Owner-Name Commonality