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Additive and Interactive Effects in Semantic Priming: Isolating Lexical and Decision Processes in the Lexical Decision Task

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The present study sheds light on the interplay between lexical and decision processes in the lexical decision task by exploring the effects of lexical decision difficulty on semantic priming effects. In 2 experiments, we increased lexical decision difficulty by either using transposed letter wordlike nonword distracters (e.g., JUGDE; Experiment 1) or by visually degrading targets (Experiment 2). Although target latencies were considerably slowed by both difficulty manipulations, stimulus quality—but not nonword type—moderated priming effects, consistent with recent work by Lupker and Pexman (2010). To characterize these results in a more fine-grained manner, data were also analyzed at the level of response time (RT) distributions, using a combination of ex-Gaussian, quantile, and diffusion model analyses. The results indicate that for clear targets, priming was reflected by distributional shifting of comparable magnitude across different nonword types. In contrast, priming of degraded targets was reflected by shifting and an increase in the tail of the distribution. We discuss how these findings, along with others, can be accommodated by an embellished multistage activation model that incorporates retrospective prime retrieval and decision-based mechanisms.

Keywords: visual word recognition, semantic priming, response time distributional analyses, ex-Gaussian analysis, diffusion model

Visual word recognition has been the focus of considerable research, with the lexical decision task being the most commonly used task to study visual word recognition (Murray & Forster, 2004), featured in thousands of studies (Gomez, in press). Importantly, lexical decision performance has been central to influential models that focus on *lexical* processing as well as models that focus on *decision* mechanisms. The former include the multistage activation model (Borowsky & Besner, 1993) and the multiple read-out model (MROM; Jacobs & Grainger, 1994), whereas the latter include the two-stage model (Balota & Spieler, 1999), the random walk model (Stone & Van Orden, 1993), the diffusion model (Ratcliff, Gomez, & McKoon, 2004), and the leaky competing accumulator model (Dufau, Grainger, & Ziegler, 2012). In addition, more recent models such as the Bayesian reader model (Norris, 2006, 2009) have attempted to unify word recognition and decision-making processes within an integrated framework that likens readers to optimal Bayesian decision makers.

In the present study, we investigate the roles of lexical and decision processes in the lexical decision task by examining the joint effects of *semantic priming* with two variables known to strongly modulate lexical decision performance: *stimulus quality* and *nonword type*. The *semantic priming effect* is the well-known finding that words preceded by related primes (e.g., NURSE–DOCTOR) are recognized faster than those preceded by unrelated primes (e.g., BUTTER–DOCTOR; Meyer, Schvaneveldt, & Ruddy, 1975). Stimulus quality refers to whether items are presented clearly or in a degraded manner; clear words are responded to faster and more accurately than degraded words (Becker & Killion, 1977). Nonword type refers to the similarity of the nonword distracters to the word targets, and the general finding is that lexical decision responses to words are slower and less accurate when more wordlike distracters are used (Stone & Van Orden, 1993).

Semantic Priming, Stimulus Quality, and Nonword Type

Several studies (Balota, Yap, Cortese, & Watson, 2008; Borowsky & Besner, 1993; Brown & Besner, 2002; Meyer et al., 1975; Thomas, Neely, & O'Connor, 2012) have observed larger semantic priming effects for degraded targets than for clear targets. According to Sternberg's (1969; Roberts & Sternberg, 1993) ad-

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ditive factors logic, two factors that produce a statistical interaction exert their influence on at least one common processing stage. In contrast, if two factors yield additive effects (i.e., two main effects without an interaction), they influence different stages (although see McClelland, 1979, for an alternative explanation of additive effects). The overadditive Stimulus Quality × Priming interaction is thus consistent with the idea that semantic priming and stimulus quality influence at least one common processing stage. Interestingly, although semantic priming interacts with stimulus quality, word-frequency and stimulus quality produce clear additive effects in lexical decision, suggesting that these two factors influence separate stages (Yap & Balota, 2007). Given that word-frequency also interacts with semantic priming (see Becker, 1979), this collective set of findings has represented an important conundrum for any comprehensive model of lexical decision performance to accommodate.

The interaction between stimulus quality and priming suggests that other experimental manipulations (e.g., stimulus degradation) that make it more difficult to discriminate between words and nonwords should also magnify priming effects. As described earlier, another way to vary lexical decision difficulty is to manipulate the similarity of nonword distracters to real words. Nonwords can be orthographically *illegal* (e.g., BRNAE), orthographically *legal* (e.g., BRONE), or homophonous with real words (i.e., *pseudohomophones*; e.g., BRANE). As nonwords become increasingly wordlike, lexical decision latencies become slower. More importantly, nonword type strongly interacts with other variables that influence lexical decision performance. For example, word-frequency effects are much larger in the presence of pseudohomophones, compared to legal or illegal nonwords (Stone & Van Orden, 1993; Yap, Balota, Cortese, & Watson, 2006).

Interestingly, Lupker and Pexman (2010) have recently demonstrated that increasing lexical decision difficulty by using wordlike nonwords (e.g., BRANE), compared to less wordlike nonwords (e.g., BRONE), did *not* alter the size of the semantic priming effect (see also Yap, Tse, & Balota, 2009). The additive effects of priming and nonword type are puzzling, in light of the Stimulus Quality × Priming, Nonword Type × Word-Frequency, and the Word-Frequency × Priming interactions. Specifically, if using more wordlike distracters increases lexical decision difficulty, and increased lexical decision difficulty is reflected in greater priming (as reflected by the Stimulus Quality × Semantic Priming interaction), then it is surprising that priming effects are *not* moderated by nonword type. Indeed, Lupker and Pexman have pointed out that the additive effects of nonword type and priming constitute another major challenge to any model that attempts to explain nonword type and semantic priming effects in lexical decision using a common lexical mechanism.

To our knowledge, the counterintuitive dissociation between the Priming × Stimulus Quality interaction and the additive effects of priming and nonword type has not been systematically investigated within a single study. More importantly, no extant model can handle these findings. For example, although the multistage interactive activation model (Borowsky & Besner, 1993) is able to accommodate the complex joint effects of stimulus quality, priming, and word-frequency, it is silent on nonword type effects. In contrast, lexical decision models that can accommodate the joint effects of nonword type with other variables—such as Balota and Chumbley's (1984) two-stage model, Grainger and Jacobs's (1996) MROM, Ratcliff et al.'s (2004) diffusion model, and Norris's (2006, 2009) Bayesian reader model—have not yet explicitly addressed the joint effects of nonword type with either stimulus quality or priming.

Objectives of the Present Study

In the present study, we reexamined the joint effects of priming with stimulus quality and nonword type. Although different groups have already reported that priming and stimulus quality interact (e.g., Balota et al., 2008) and that priming and nonword type are additive (Lupker & Pexman, 2010), comparing studies that employ different sets of stimuli or participants with different levels of vocabulary knowledge (i.e., knowledge of word forms and meanings) could be potentially misleading. For example, although the overadditive interaction between priming and word-frequency (i.e., stronger priming for low-frequency words) is considered a benchmark finding in the word recognition literature (see McNamara, 2005; Neely, 1991), Yap et al. (2009) recently demonstrated that the interaction between priming and word-frequency was observed only for participants with *less* vocabulary knowledge, whereas participants with *more* vocabulary knowledge produced additive effects. To ensure that any observed effects in the present study are not driven by differences in stimuli difficulty or participants' vocabulary knowledge, the same prime-target pairs were used across experiments, and participants in the different experiments were matched on vocabulary knowledge (as reflected by performance on a standardized vocabulary measure).

More importantly, the present study also afforded the opportunity to explore the effects of the targeted variables on both mean response times (RTs) and the underlying characteristics of RT distributions. Although chronometric studies of cognitive processing overwhelmingly examine RTs at the level of the mean, there is mounting evidence that experimental variables can selectively modulate different characteristics of empirical RT distributions (see Balota & Yap, 2011, for a review). A popular way to carry out distributional analyses is to fit empirical RT data to a theoretical distribution like the ex-Gaussian function, which is the convolution of a Gaussian (normal) and exponential distribution (Ratcliff, 1979). The ex-Gaussian distribution contains three parameters; μ and σ, respectively, reflect the mean and standard deviation of the Gaussian distribution, whereas τ reflects the mean and standard deviation of the exponential distribution. Changes in μ indicate distributional shifting, whereas changes in τ reflect modulations in the tail of the distribution. Ex-Gaussian analysis is usually supplemented by a nonparametric technique called Vincentizing (Ratcliff, 1979), through which one can examine the effect of a variable on different regions of the RT distribution. To carry out Vincentizing, one first rank orders each participant's RTs separately for each condition, followed by computing effects at different quantiles (e.g., .1, .2, .3, .4, etc.). These tools collectively allow researchers to ascertain whether effects are mediated by distributional shifting, an increase in the slow tail of the distribution, or some combination of both.

Importantly, RT distributional analyses have yielded new insights into the nature of semantic priming. For example, Balota et al. (2008) demonstrated that when targets are presented clearly, the semantic priming effect for highly skilled lexical processors is reflected by a shift in the RT distribution (see Figure 1). However,

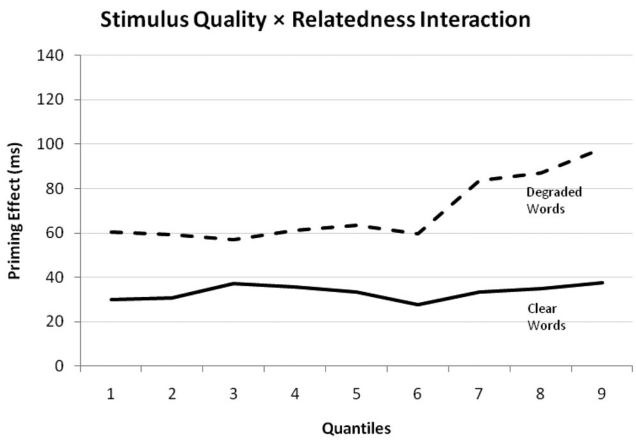

Figure 1. Interactive effects of Stimulus Quality and Relatedness across quantiles, showing that the larger effects of priming for degraded, compared to clear, targets are due to both a shift and a stretching in the tail of the distribution.

when the same targets are visually degraded, priming simultaneously shifts *and* increases the tail of the distribution, and this is reflected in more priming for the slower, more difficult trials (see Figure 1). Balota et al. have argued that these results are consistent with the idea that for highly fluent lexical processors, semantic priming for clearly presented words is mediated by a relatively modular head-start mechanism, where primes simply speed up recognition of the related target by some constant amount of time, regardless of target difficulty (for a similar effect on eye fixation durations, see Staub, 2011). In contrast, when targets are degraded, the system adaptively recruits any information available to help resolve the target (Whittlesea & Jacoby, 1990) and is therefore more reliant on prime information for the more difficult items, which is reflected in the slower quantiles of the RT distribution. To our knowledge, how nonword type moderates priming at the level of RT distributions has not been investigated. The study by Lupker and Pexman (2010), which has addressed this question most directly among extant studies (e.g., Joordens & Becker, 1997; Milota, Widau, McMickell, Juola, & Simpson, 1997; Stone & Van Orden, 1992), was based on mean RT analyses.

Although ex-Gaussian parameters help provide a finer-grained summary of empirical RT distributions, it is inappropriate, without a theoretical framework, to directly map them onto cognitive processes (Matzke & Wagenmakers, 2009). To better understand the underlying mechanisms, researchers (e.g., Balota & Spieler, 1999; Schmiedek, Oberauer, Wilhelm, Süß, & Wittmann, 2007) have recommended fitting RT data to process-oriented models such as the diffusion model of binary decision (Ratcliff, 1978; Ratcliff et al., 2004). According to the diffusion model, lexical decision involves the accumulation of noisy information over time from a starting point toward one of two decision boundaries (word or nonword). Three major parameters describe this process. *Drift rate* (v) refers to the mean rate at which information is accumulated from the word or nonword stimulus, *boundary separation* (a) refers to the location of the response criterion, and T_{er} refers to the nondecision component that collectively indexes encoding and response execution processes. Importantly, this model allows one to distinguish between the quality of evidence driving the decision, the decision criteria, and nondecision processes (Ratcliff, Thapar, & McKoon, 2010). In order to capitalize on the additional insights afforded by diffusion model parameter estimates, distributional effects in the present study are explored using a combination of ex-Gaussian analysis, Vincentizing, and diffusion model analysis.

To recapitulate, the present study uses the same participant pool and stimulus set to directly compare two manipulations of lexical decision difficulty (i.e., nonword type vs. stimulus quality) on semantic priming, and by analyzing these effects both at the level of the mean and at the level of underlying RT distributional characteristics. Specifically, in Experiment 1, we compare priming effects when legal versus transposed-letter (TL) nonwords (e.g., TR*IA*N) are used. It is important to replicate the intriguing additive pattern observed by Lupker and Pexman (2010), given some of the mixed findings previously reported in this literature (e.g., Milota et al., 1997; Shulman & Davison, 1977). TL nonwords are created by transposing two letters in a word (e.g., TRAIN–TRIAN) and are perceptually very similar to real words (Forster, Davis, Schoknecht, & Carter, 1987; Perea & Lupker, 2003). Crucially, TL nonwords slow participants down even more effectively than pseudohomophones (Lupker & Pexman, 2010; see also Perea & Lupker, 2004).

In Experiment 2, we compare priming effects when clear versus degraded targets are presented. Stimuli are degraded by rapidly alternating the target letter string (e.g., DOG) with a randomly generated mask of the same length (e.g., &?#). This paradigm yields robust degradation effects (e.g., Balota et al., 2008; Yap & Balota, 2007; Yap, Balota, Tse, & Besner, 2008) that are qualitatively similar to those produced by other degradation manipulations (e.g., contrast reduction; O'Malley, Reynolds, & Besner, 2007). A within-participant manipulation of stimulus quality is used, consistent with other studies manipulating this variable (Balota et al., 2008; Becker & Killion, 1977; Besner & Smith, 1992; Borowsky & Besner, 1993; Brown, Stolz, & Besner, 2006; O'Malley et al., 2007; Plourde & Besner, 1997).

Experiment 1

Method

Participants. Eighty participants (58 females) from the National University of Singapore participated for course credit. All participants were proficient in English and had normal or corrected-to-normal vision. The mean vocabulary age, as measured by the vocabulary subscale of the Shipley Institute of Living Scale (Shipley, 1940), was 18.08 (SD = 0.82).

Design. Priming (related or unrelated) was manipulated within-participants, and Nonword Type (legal nonwords or TL nonwords) was manipulated between-participants; half the participants were presented with legal nonwords, whereas the other half were presented with TL nonwords.

Stimuli. One hundred twenty words (see the Appendix for a full list of stimuli) served as targets (see Table 1 for descriptive statistics). Each target word was preceded by either a related or unrelated prime, yielding 60 observations per participant cell. Across participants, stimuli were counterbalanced across the related and unrelated conditions; unrelated prime-word target pairs were created by re-pairing the primes and targets within each set. No prime or target was repeated within

Table 1
Descriptive Statistics for the Word and Nonword Stimuli Used in Experiments 1 and 2

Word stimuli (N = 120)	M	SD
Number of morphemes	1.34	0.51
Number of syllables	1.79	0.73
Number of letters	6.14	1.67
Number of phonemes	5.10	1.70
Log HAL frequency (Lund & Burgess, 1996)	8.07	1.13
Number of orthographic neighbors	2.64	3.91
Number of phonological neighbors	5.75	8.15
Orthographic Levenshtein distance (Yarkoni et al., 2008)	2.17	0.71
Phonological Levenshtein distance (Yap & Balota, 2009)	2.03	0.83
Forward associative strength (Nelson et al., 2004)	0.21	0.18
Backward associative strength (Nelson et al., 2004)	0.16	0.21

Nonword stimuli (N = 120)	Legal nonwords		TL nonwords	
Log HAL baseword frequency (Lund & Burgess, 1996)			8.10	1.37
Number of syllables	1.76	0.73	1.76	0.69
Number of letters	6.16	1.65	6.14	1.67
Number of orthographic neighbors	2.67	3.95	2.73	3.8

Note. HAL = Hyperspace Analogue to Language; TL = transposed-letter.

a participant. Legal nonwords and the base words from which TL nonwords were derived were matched to target words on number of syllables, letters, and orthographic neighbors (see Table 1). One hundred and twenty legal nonwords were obtained from the English Lexicon Project (Balota et al., 2007), whereas 120 TL nonwords were obtained by rearranging two adjacent letters in words. Four TL nonwords were obtained by transposing the first and second letters, 23 by transposing the second and third letters, 47 by transposing the third and fourth letters, 31 by transposing the fourth and fifth letters, 10 by transposing the fifth and sixth letters, 4 by transposing the sixth and seventh letters, and 1 by transposing the seventh and eighth letters.

Procedure. PC-compatible computers running E-prime software (Schneider, Eschman, & Zuccolotto, 2001) were used for stimulus presentation and data collection. All stimuli were displayed in the center of the computer screen, and participants' responses were made on a computer keyboard. Participants were tested individually in sound-attenuated cubicles, sitting about 60 cm from the screen. They first provided demographic information (gender, race, age, and years of university education) and completed the vocabulary subscale (40 item vocabulary test) of the Shipley Institute of Living Scale (Shipley, 1940; Zachary, 1992) on the computer. Participants were instructed that a word and a letter string would be presented sequentially and they were to decide whether the letter string formed a word or nonword by making the appropriate button press, that is, the apostrophe key for words and the A key for nonwords. Participants were encouraged to respond quickly but not at the expense of accuracy. There were 20 practice trials, followed by four experimental blocks of 60 trials each, with breaks between blocks. The order in which stimuli were presented was randomized anew for each participant. Stimuli were presented in uppercase 14-point Courier New, and each trial comprised the following order of events: (a) a fixation point (+) at the center of the monitor for 2,000 ms, (b) the prime for 150 ms, (c) a blank screen for 650 ms, and (d) the target, resulting in an 800-ms prime-target stimulus onset asynchrony. The target remained on the screen for 3,000 ms or until a response was made. Each correct response was followed by an intertrial interval of 450 ms. If a response was incorrect, a 170-ms tone was presented simultaneously with the word "Incorrect" displayed slightly below the fixation point for 450 ms.

Results and Discussion

Errors (5.7% across all conditions) were first excluded from the analyses. In addition, responses below 200 ms and above 3,000 ms were eliminated before a standard deviation was calculated for each participant. Response latencies beyond 2.5 *SD*s from each participant's mean were also excluded, and this removed a further 2.8% of the responses. The mean RTs, accuracy rates, and ex-Gaussian parameters are presented in Table 2.

Table 2
Mean RTs, Accuracy, Ex-Gaussian, and Diffusion Model Parameters as a Function of Nonword Type and Relatedness in Experiment 1

Nonword type/priming	M	Accuracy	μ	σ	τ	v	a	T_{er}
Legal nonwords								
Related	606	0.98	479	52	128	3.32	1.49	0.39
Unrelated	625	0.96	499	46	127	3.30	1.47	0.41
Priming effect	19	0.02	20	−6	−1	0.02	−0.02	0.02
TL nonwords								
Related	764	0.96	531	62	235	2.58	1.88	0.40
Unrelated	782	0.96	545	53	238	2.52	1.86	0.43
Priming effect	18	0	14	−9	3	0.06	−0.02	0.03
Interaction	−1	−0.02	−6	−3	4	0.04	0	0.01

Note. RT = response time; TL = transposed-letter.

Response latencies. For RTs, the main effects of nonword type, $F_p(1, 78) = 25.62$, $p < .001$, $MSE = 38{,}866$, $\eta_p^2 = .25$; $F_i(1, 119) = 368.96$, $p < .001$, $MSE = 8{,}318$, $\eta_p^2 = .76$, and priming, $F_p(1, 78) = 12.75$, $p = .001$, $MSE = 1{,}038$, $\eta_p^2 = .14$; $F_i(1, 119) = 12.39$, $p = .001$, $MSE = 3{,}784$, $\eta_p^2 = .09$, were significant. The Nonword Type × Priming interaction did not approach significance by participants or by items, Fs < 1.

Accuracy rates. For accuracy rates, the main effect of nonword type was significant by items and approached significance by participants, $F_p(1, 78) = 2.81$, $p = .098$, $MSE = 0.002$, $\eta_p^2 = .035$; $F_i(1, 119) = 5.52$, $p = .020$, $MSE = 0.002$, $\eta_p^2 = .044$. The main effect of priming, $F_p(1, 78) = 5.67$, $p = .020$, $MSE = 0.001$, $\eta_p^2 = .068$; $F_i(1, 119) = 5.19$, $p = .025$, $MSE = 0.002$, $\eta_p^2 = .042$, and the Nonword Type × Priming interaction, $F_p(1, 78) = 6.30$, $p = .014$, $MSE = 0.001$, $\eta_p^2 = .075$; $F_i(1, 119) = 4.69$, $p = .032$, $MSE = 0.002$, $\eta_p^2 = .038$, were also significant. As shown in Table 2, the priming effect was larger in the context of legal nonwords compared to TL nonwords.

Ex-Gaussian analyses. Using the quantile maximum likelihood estimation (QMLE) procedure in the QMPE v2.18 program (Cousineau, Brown, & Heathcote, 2004; Heathcote, Brown, & Mewhort, 2002), ex-Gaussian parameters (μ, σ, τ) were obtained for each participant across the different experimental conditions. QMLE provides unbiased parameter estimates and has been demonstrated to be more effective than continuous maximum likelihood estimation for small samples (Heathcote & Brown, 2004; Speckman & Rouder, 2004). All fits successfully converged within 250 iterations.

For μ, the main effects of nonword type, $F(1, 78) = 8.37$, $p = .005$, $MSE = 11{,}563$, $\eta_p^2 = .10$, and priming, $F(1, 78) = 22.02$, $p < .001$, $MSE = 539$, $\eta_p^2 = .22$, were significant. The Nonword Type × Priming interaction was not significant, $F < 1$. Turning to σ, only the main effect of priming was significant, $F(1, 78) = 5.68$, $p = .020$, $MSE = 424$, $\eta_p^2 = .07$. Finally, for τ, only the main effect of nonword type was significant, $F(1, 78) = 33.67$, $p < .001$, $MSE = 13{,}962$, $\eta_p^2 = .30$.

Quantile analyses (Vincentizing). The mean quantiles for the different experimental conditions are plotted in Figure 2, whereas Figure 3 presents priming effects as a function of nonword type. In Figure 2, the empirical quantiles are represented by data points and standard error bars, and the estimated quantiles for the best-fitting ex-Gaussian distribution are represented by lines.

The theoretical quantiles were estimated for each condition by using Monte Carlo simulations to generate ex-Gaussian distributions (comprising 20,000 observations for each condition) corresponding to the ex-Gaussian parameters for that condition (see White & Staub, 2011). The goodness of fit between the empirical and theoretical quantiles reflects the extent to which the empirical RT distributions are being captured by the ex-Gaussian parameters. From Figure 3, it is clear that priming effects in the legal and TL nonword conditions are approximately the same size and remain relatively invariant across the quantiles.

Diffusion model analyses. To obtain diffusion model parameter estimates, we used the e Fast-dm program (Voss & Voss, 2007), which uses the partial differential equation (PDE) method (Voss & Voss, 2008) to estimate diffusion model parameters efficiently and accurately. Across experimental conditions, Fast-dm was used to estimate drift rate (v), boundary separation (a), and the nondecision component (T_{er}) for each participant. For v, larger numbers reflect steeper drift rates; for a, larger numbers reflect more conservative response criteria; and for T_{er}, larger numbers reflect longer nondecision times.

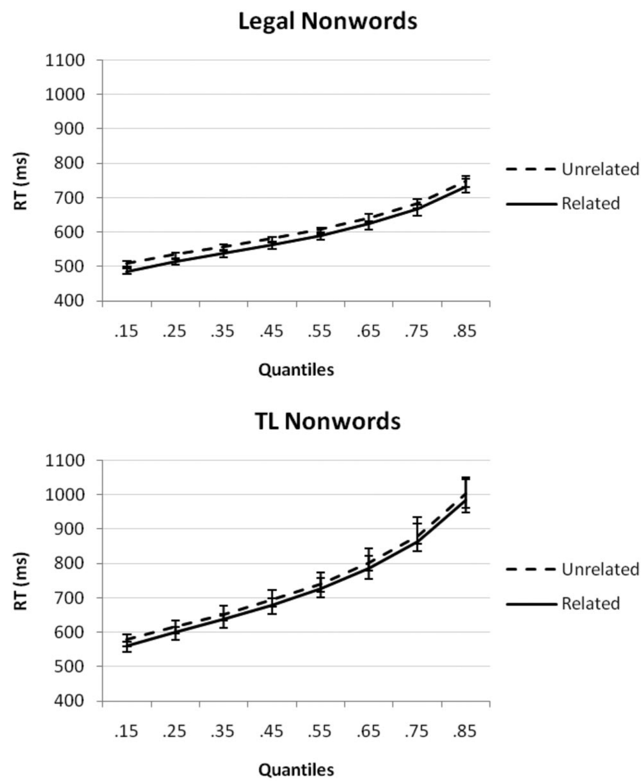

Figure 2. Lexical decision performance from Experiment 1 as a function of Relatedness and Quantiles in the legal nonword condition (top panel) and transposed-letter (TL) nonword condition (bottom panel). Empirical quantiles are represented by error bars, whereas fitted ex-Gaussian quantiles are represented by lines. RT = response time.

For v, only the main effect of nonword type was significant, $F(1, 78) = 30.81$, $p < .001$, $MSE = 0.751$, $\eta_p^2 = .28$; none of the other effects were reliable, Fs < 1. For a, only the main effect of nonword type was significant, $F(1, 78) = 29.69$, $p < .001$, $MSE = 0.200$, $\eta_p^2 = .28$; none of the other effects were reliable, Fs < 1. For T_{er}, only the main effect of priming was significant, $F(1, 78) = 11.43$, $p = .001$, $MSE = 0.003$, $\eta_p^2 = .13$; none of the other effects were reliable, ps $> .25$.

Summary. Although the presence of TL nonword distracters substantially slowed responses to word targets, priming effects were not moderated by nonword type, replicating Lupker and Pexman (2010). Furthermore, distributional analyses revealed that priming—for both nonword types—was reflected only by distributional shifting (μ), whereas nonword type effects—for related and unrelated targets—were reflected by shifting (μ) and an increase in the tail (τ) of the distribution. Finally, the diffusion model analyses indicated that the distributional shift associated with priming was mediated entirely by nondecision time (T_{er}; i.e., the time taken for encoding and response execution), not by drift rate (v) or boundary separation (a). In contrast, the effect of nonword type was reflected in lower drift rates and more conservative response criteria when TL nonwords were used as distracters.

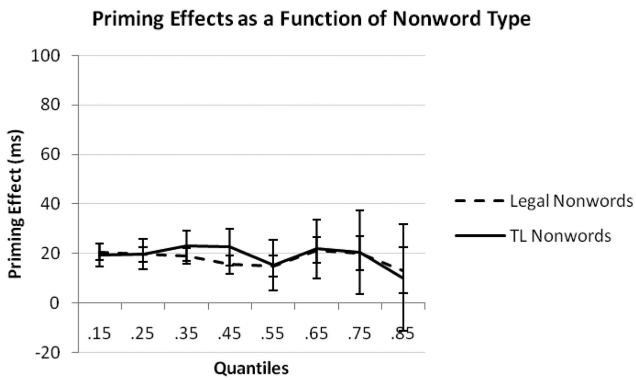

Figure 3. Priming effect across quantiles as a function of nonword type. Error bars reflect the standard errors of the difference scores. TL = transposed-letter.

Experiment 2

Method

Participants. Forty-eight participants (30 females) from the National University of Singapore participated for course credit. All participants were proficient in English and had normal or corrected-to-normal vision. The mean vocabulary age, as measured by Shipley's (1940) Vocabulary subscale, was 17.90 (*SD* = 1.11).

Design. Priming (related or unrelated) and Stimulus Quality (clear or degraded) were manipulated within-participants. The dependent variables were RT and accuracy.

Stimuli. The 120 prime-target pairs and legal nonwords from Experiment 1 were used.

Procedure. The procedure of Experiment 2 was similar to that used in Experiment 1, except that for half the trials (i.e., the degraded condition), letter strings were rapidly alternated with a randomly generated mask of the same length. For example, the mask @$#&% was presented for 14 ms, followed by a five-letter target word for 28 ms, and the two repeatedly alternated until the participant responded. The masks were generated from random permutations of the following symbols: &@?!$*%#?>. Across participants, targets were counterbalanced across related and unrelated conditions and degraded and clear conditions.

Results and Discussion

Errors (6.3% across all conditions) and response latencies shorter than 200 ms or longer than 3,000 ms were excluded from the analyses. Response latencies beyond 2.5 *SD*s from each participant's mean were also excluded, removing an additional 3.4% of the responses. The mean RTs, accuracy rates, and ex-Gaussian parameters are presented in Table 3.

Response latencies. For RTs, the main effects of stimulus quality, $F_p(1, 47) = 96.55$, $p < .001$, $MSE = 9{,}791$, $\eta_p^2 = .67$; $F_i(1, 119) = 486.21$, $p < .001$, $MSE = 5{,}123$, $\eta_p^2 = .80$, and priming, $F_p(1, 47) = 35.37$, $p < .001$, $MSE = 2{,}582$, $\eta_p^2 = .43$; $F_i(1, 119) = 25.23$, $p < .001$, $MSE = 9{,}222$, $\eta_p^2 = .18$, were significant. The Stimulus Quality × Priming interaction was also significant, $F_p(1, 47) = 8.92$, $p = .004$, $MSE = 2{,}467$, $\eta_p^2 = .16$; $F_i(1, 119) = 12.05$, $p = .001$, $MSE = 6{,}420$, $\eta_p^2 = .09$. Priming effects were larger for degraded (65 ms) than for clear (22 ms) targets.

Accuracy rates. For accuracy rates, the main effects of stimulus quality, $F_p(1, 47) = 29.70$, $p < .001$, $MSE = 0.002$, $\eta_p^2 = .39$; $F_i(1, 119) = 11.55$, $p = .001$, $MSE = 0.015$, $\eta_p^2 = .088$, and priming, $F_p(1, 47) = 12.81$, $p = .001$, $MSE = 0.002$, $\eta_p^2 = .21$; $F_i(1, 119) = 11.76$, $p = .001$, $MSE = 0.006$, $\eta_p^2 = .090$, were significant. The Stimulus Quality × Priming interaction approached significance by participants and by items, $F_p(1, 47) = 2.99$, $p = .090$, $MSE = 0.002$, $\eta_p^2 = .06$; $F_i(1, 119) = 3.38$, $p = .069$, $MSE = 0.005$, $\eta_p^2 = .028$. Priming effects were larger for degraded (3.6%) than for clear (1.3%) targets.

Ex-Gaussian analyses. For μ, the main effects of stimulus quality, $F_p(1, 47) = 83.81$, $p < .001$, $MSE = 3{,}021$, $\eta_p^2 = .64$, and priming, $F_p(1, 47) = 13.05$, $p = .001$, $MSE = 2{,}599$, $\eta_p^2 = .22$, were significant. The Stimulus Quality × Priming interaction was not significant, $F < 1$. Turning to σ, none of the effects were reliable, *F*s < 1. Finally, for τ, the main effect of stimulus quality was significant, $F(1, 47) = 20.16$, $p < .001$, $MSE = 11{,}001$, $\eta_p^2 = .30$, but the main effect of priming did not reach significance ($p = .096$). This was qualified by a borderline reliable Stimulus Quality × Priming interaction, $F(1, 47) = 3.60$, $p = .064$, $MSE = 3{,}162$, $\eta_p^2 = .07$, where priming effects were larger for degraded (30 ms) than for clear (−1 ms) targets.

Quantile analyses. The mean quantiles for the different experimental conditions are plotted in Figure 4, whereas Figure 5 presents priming effects as a function of stimulus quality. From

Table 3
Mean RTs, Accuracy, Ex-Gaussian, and Diffusion Model Parameters as a Function of Stimulus Quality and Relatedness in Experiment 2

Stimulus quality/priming	*M*	Accuracy	μ	σ	τ	*v*	*a*	T_{er}
Clear								
Related	650	0.97	508	55	145	2.78	1.34	0.43
Unrelated	672	0.96	531	61	144	2.88	1.34	0.45
Priming effect	22	0.01	23	6	−1	−0.10	0	0.02
Degraded								
Related	769	0.94	577	63	198	2.50	1.47	0.51
Unrelated	834	0.91	608	61	228	2.23	1.54	0.53
Priming effect	65	0.03	31	−2	30	0.27	0.07	0.02
Interaction	43	0.02	8	−8	31	0.37	0.07	0

Note. RT = response time.

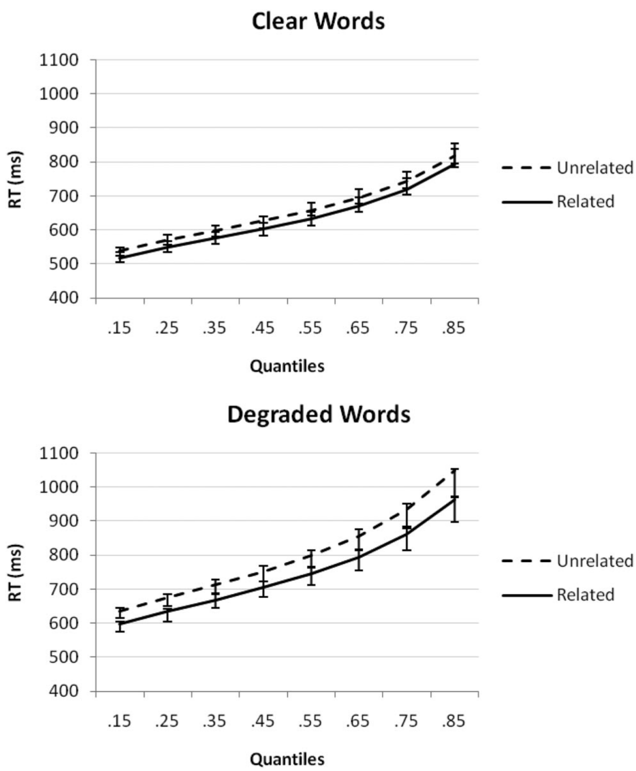

Figure 4. Lexical decision performance from Experiment 2 as a function of Relatedness and Quantiles in the clear condition (top panel) and degraded condition (bottom panel). Empirical quantiles are represented by error bars, whereas fitted ex-Gaussian quantiles are represented by lines. RT = response time.

Figure 4, it is clear that priming effects for clear targets remained relatively constant across the quantiles, but priming effects for degraded targets increased across the RT distribution.

Diffusion model analyses. For *v*, the main effect of stimulus quality, $F(1, 47) = 53.05$, $p < .001$, $MSE = 0.200$, $\eta_p^2 = .53$, was significant. The Stimulus Quality × Priming interaction was also significant, $F(1, 47) = 8.02$, $p = .007$, $MSE = 0.200$, $\eta_p^2 = .15$; priming effects were reliable for degraded ($p = .002$) but not for clear ($p = .379$) targets. Moreover, degradation effects were reliable for both related and unrelated targets (*p*s < .01), with stronger degradation effects observed for unprimed words. Turning to *a*, only the main effect of stimulus quality was significant, $F(1, 47) = 19.09$, $p < .001$, $MSE = 0.069$, $\eta_p^2 = .29$; none of the other effects were reliable, *p*s > .19. For T_{er}, the main effects of stimulus quality, $F(1, 47) = 109.07$, $p < .001$, $MSE = 0.002$, $\eta_p^2 = .70$, and priming, $F(1, 47) = 5.95$, $p = .019$, $MSE = 0.004$, $\eta_p^2 = .11$, were significant; the Stimulus Quality × Priming interaction was not reliable, $F < 1$.

Summary. Priming effects were larger for degraded, compared to clear, words, and this interaction was predominantly mediated by τ, the tail of the distribution, consistent with the extant literature (see, e.g., Balota et al., 2008). Specifically, priming reflected a shift (μ) for clear targets, but shifting (μ) and an increase in the tail (τ) for degraded targets. The diffusion model analyses revealed that for clear targets, priming was primarily reflected by nondecision time (T_{er}), consistent with Experiment 1. However, when targets were degraded, priming was mediated by nondecision time and drift rate (*v*); compared to related targets, unrelated targets were associated with reliably lower drift rates.

General Discussion

In the present study, we explored how the well-studied semantic priming effect was moderated by two variables known to robustly increase lexical decision difficulty: nonword type (TL nonwords vs. legal nonwords) and stimulus quality (clear vs. degraded). In order to increase the clarity of our comparisons, we used a common set of prime-target pairs, and participants across different experiments were sampled from the same participant pool and were comparable on vocabulary knowledge. It is first worth noting that both manipulations strongly increased discrimination difficulty. Specifically, in Experiment 1, TL nonword distracters (e.g., JUGDE), compared to legal nonwords, slowed RTs to words by 158 ms. In Experiment 2, visually degrading words slowed RTs by 115 ms. Importantly, there was a dissociation between the effects of nonword type and stimulus quality on semantic priming. While nonword type and priming produced *additive* effects (replicating Lupker & Pexman, 2010), stimulus quality and priming interacted, yielding greater priming for degraded words. More intriguingly, distributional analyses revealed that semantic priming was reflected by shifting of comparable magnitude for legal and TL nonwords (see Figure 3). In contrast, although priming for clear targets was reflected by a shift, priming for degraded targets reflected both shifting and an increase in the tail of the distribution (see Figure 5). Supplementary diffusion model analyses also indicated that the distributional shift associated with the priming of clear targets is most consistent with changes in nondecision time, whereas the priming of degraded targets implicates changes in nondecision time and, importantly, drift rate.

Although the main effects of nonword type and stimulus quality were of secondary interest in the present study, the distributional analyses also yielded insights into how these factors influence word recognition performance. Specifically, the slowing observed in the context of difficult TL nonwords was mediated more strongly by τ (i.e., the tail of the distribution) than by μ, consistent with Yap et al. (2006). The presence of TL nonwords was also associated with lower drift rates and more conservative response

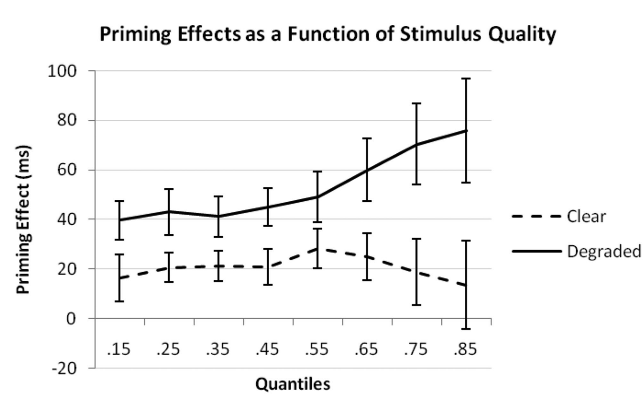

Figure 5. Priming effect across quantiles as a function of stimulus quality. Error bars reflect the standard errors of the difference scores.

criteria but had no influence on nondecision time. Turning to stimulus quality effects, the slowing afforded by degrading the stimulus was reflected to a similar extent in μ and τ (replicating Yap & Balota, 2007). In addition, degrading words resulted in lower drift rates, longer nondecision times, and more conservative response criteria.

We are not aware of any theoretical framework or model that has attempted to provide a unified explanation for the dissociations reported in the present study, along with other well-established findings in the lexical decision literature. In the remainder of this article, we discuss in greater depth how these results might be accommodated.

Joint Effects of Stimulus Quality, Priming, and Nonword Type: Going Beyond the Mean

In the present study, we examined the targeted effects both at the level of the mean and at the level of underlying RT distributional characteristics. In order to better characterize distributional effects, data were examined using a combination of ex-Gaussian, quantile, and diffusion model techniques. The results from Experiment 1 indicated that semantic priming was reflected by distributional shifting of comparable magnitude for clearly presented targets, whether legal or TL nonwords were used (see Figure 3). In terms of diffusion model parameters, this semantic priming shift was mediated by nondecision time but not by drift rate or response boundary. However, turning to Experiment 2, a different pattern was found. Specifically, when targets were degraded, priming was reflected by both shifting and an increase in the tail of the distribution (see Figure 5), consistent with an increase in nondecision time and drift rate.

The results from the diffusion model, which captures the distributional changes, are informative in a number of ways. First, the distributional shift associated with priming clear targets largely reflects an effect on the duration of the *non*decision component, which taps processes involved in stimulus encoding and response execution. Second, drift rate mediates the priming effect *only* when targets are degraded. Both of these patterns would appear to place further constraints on Ratcliff and McKoon's (1988) compound-cue model of priming, which emphasizes changes in drift rate across related and unrelated primes. Finally, whereas increasing difficulty via nonword type reliably decreased word drift rate and made participants more conservative, priming was equivalent across different types of nonwords, both at the level of the mean and at the level of distributional characteristics.

Balota et al. (2008) have argued that priming that is reflected by a shift (observed in highly skilled readers) is most consistent with a relatively modular headstart mechanism, wherein primes produce a constant amount of preactivation for the logogens (Morton, 1969) of related targets. This notion of a headstart meshes well with the finding that priming influences the nondecision (i.e., encoding and response execution) component rather than the response boundaries of a diffusion process (cf. Borowsky & Besner, 1993). It is worth noting that adjusting response boundaries can also produce distributional shifting in a simple random walk model (Spieler, Balota, & Faust, 2000; Yap et al., 2006), so it is intriguing that the diffusion model analyses attribute shifting to nondecision time. Distributional shifting cannot be easily reconciled with feature-overlap models of priming (Masson, 1995; Plaut & Booth, 2000), which predict changes in the scale of the RT distribution (i.e., slower trials should be associated with more priming). As noted, the compound-cue model also assumes that priming effects are generally mediated by changes in drift rate, which is of course inconsistent with the present observation that priming as reflected by drift rate variations is observed only for degraded targets.

When targets are visually degraded, priming is reflected by both shifting *and* an increase in the tail of the distribution. Consistent with this, supplementary diffusion model analyses revealed that priming for degraded targets involved changes in nondecision time and drift rate. To explain this, Balota et al. (2008) have proposed that degraded targets are difficult to resolve, and the lexical system therefore adaptively retrieves more prime information when processing such targets (for an adaptive rational analysis of semantic priming, also see Anderson & Milson, 1989; Bodner, Masson, & Richard, 2006). Moreover, the distributional plots (see Figure 5) indicate that reliance on prime information is proportional to the difficulty of the trial. Therefore, the more difficult items—that is, those at the slow end of the RT distribution—are associated with more priming. This suggests that when a target is degraded, priming reflects both a headstart and an additional prime retrieval mechanism that is engaged *after* the target is presented and which is flexibly modulated by the fluency of target processing (see Balota & Yap, 2006, for a discussion of flexible lexical processing).

The distinction between priming as a headstart and priming as a flexible prime retrieval process aligns nicely with the distinction between prospective versus retrospective priming mechanisms (Thomas et al., 2012). Prospective priming refers to the facilitation afforded by a prime *before* a target is presented (e.g., Balota et al., 2008), whereas retrospective priming (e.g., Balota et al., 2008; Bodner & Masson, 1997; Neely, Keefe, & Ross, 1989; Ratcliff & McKoon, 1988) implicates processes that operate *after* the target is presented. In this light, distributional shifting might be viewed as a marker for prospective priming mechanisms, whereas an increase in the distribution's tail may reflect a more strategic retrospective mechanism. Interestingly, Thomas et al. (2012) recently explored the effect of prime-target associative direction on the Stimulus Quality × Priming interaction. Prospective priming mechanisms necessarily depend on the presence of a forward prime-to-target association (e.g., KEG–BEER) and cannot account for backward priming (i.e., target-to-prime association; e.g., SMALL–SHRINK). Thomas et al. reported that the overadditive interaction between stimulus quality and priming was seen for trials with symmetric (e.g., EAST–WEST) or backward (target-to-prime) associations but was not seen for trials with only forward (prime-to-target) associations. This suggests that the Stimulus Quality × Priming interaction is entirely mediated by a retrospective prime retrieval mechanism that depends on the presence of a backward target-to-prime association. We comment more on this intriguing finding later.

Dissociating Nonword Type and Stimulus Quality Effects: Implications for Models

We now consider the broader theoretical implications of our findings for models of word recognition and lexical decision performance. The present study was motivated by an intriguing dissociation reported by Lupker and Pexman (2010), wherein the joint effects of nonword type and frequency were very different from the joint effects of nonword type and semantic priming. That is, whereas frequency effects became larger in the presence of TL nonwords, priming effects remained the same size. According to Lupker and Pexman, any model that accounts for nonword type effects in lexical decision performance using a single, lexically driven mechanism is hard pressed to account for this pattern. These include the MROM (Grainger & Jacobs, 1996), the diffusion model (Ratcliff et al., 2004), and the Bayesian reader model (Norris, 2006, 2009).

First, let us consider how the three models capture the frequency by nonword type interactions. In the MROM, lexical decisions to *words* are made when the activation level of individual lexical representations (i.e., local activity) or the summed activation of all representations (i.e., global activity) exceed their respective thresholds. The response threshold for global activation, also known as the σ criterion, is set higher as nonword distracters become more wordlike. This implies that as nonword wordlikeness increases, word responses are influenced to a greater extent by local, relative to global, lexical activity, resulting in longer latencies. Importantly, variations in the σ criterion (as a function of nonword type) exert more influence on low-frequency than on high-frequency words, yielding larger frequency effects in the context of wordlike nonwords. Turning to the diffusion model (Ratcliff et al., 2004), nonword context has a greater impact on the drift rate of low-frequency words than on the drift rate of high-frequency words. Consequently, the difference between the drift rates of high- and low-frequency words is magnified as distracters become more wordlike. Finally, in the Bayesian reader model (Norris, 2006, 2009), the model continuously computes the ratio of the summed likelihood that the presented letter string is a word to the summed likelihood that it is a nonword; evidence for a word response accumulates more rapidly as this ratio becomes larger. Increasing distracter wordlikeness increases the nonword likelihood, which slows down lexical decision to both words and nonwords. Indeed, the Bayesian reader successfully simulates the Nonword Type × Word-Frequency interaction (see Norris, 2009, for more details).

In short, the three single-process models described above can accommodate the well-known interaction between nonword type and word-frequency. With the exception of the diffusion model, which accounts for word-frequency (Ratcliff et al., 2004) and priming (Ratcliff & McKoon, 1988) effects via drift rate changes, the other models have not yet been extended to explicitly account for semantic priming effects. However, priming effects could, in principle, reflect the same mechanisms underlying frequency effects. Specifically, just as activation thresholds (or resting activation levels) are lower for high-frequency words, compared to low-frequency words, activation thresholds (or resting activation levels) could be lower for targets primed by related words, compared to targets primed by unrelated words. However, as Lupker and Pexman (2010) have correctly pointed out, if priming and frequency effects indeed implicate a common lexical mechanism, then semantic priming should also interact with nonword type, a prediction that is clearly at odds with their findings and the results of Experiment 1.

In addition to the problems posed for the extant models by the differential effect of nonword difficulty on semantic priming and word-frequency effects, one finds a qualitatively different pattern when one considers increasing lexical decision difficulty by degrading the target. The Stimulus Quality × Priming interaction (explored in Experiment 2), which at the level of the mean has been replicated by various investigators (e.g., Balota et al., 2008; Borowsky & Besner, 1993; Brown & Besner, 2002; Meyer et al., 1975; Thomas et al., 2012), in conjunction with the well-known additive effects of stimulus quality and frequency (Balota & Abrams, 1995; Becker & Killion, 1977; Plourde & Besner, 1997; Stanners, Jastrzembski, & Westbrook, 1975; Yap & Balota, 2007) provide an interesting counterpoint to the intriguing relationships between nonword type, frequency, and priming. Remarkably, nonword type is additive with priming but interactive with frequency, whereas stimulus quality is additive with frequency but interactive with priming. Again, if one assumes that frequency and priming effects implicate a common lexical locus, then it is not obvious why stimulus quality is additive with the former and interactive with the latter.

Possibly, one needs to consider a completely different perspective to account for this complex pattern of results. Plaut and Booth (2000) proposed a single-mechanism parallel distributed processing (PDP) model, in which input and output processes are mediated by a nonlinear sigmoid function. The full details of this model are beyond the scope of this report, but essentially, the nonlinear function allows equal differences in the input to be reflected by equal or unequal differences of the output, depending on the portion of the function being considered (see Figure 6). Words and nonwords are discriminated on the basis of *semantic stress* (a measure of familiarity); words, compared to nonwords, are associated with higher stress values. Hence, this connectionist model, unlike the single-process models described above, can potentially accommodate the complex joint effects of stimulus quality, word-frequency, and semantic priming. Although Plaut and Booth have explicitly mentioned that the *specific* implemented model they

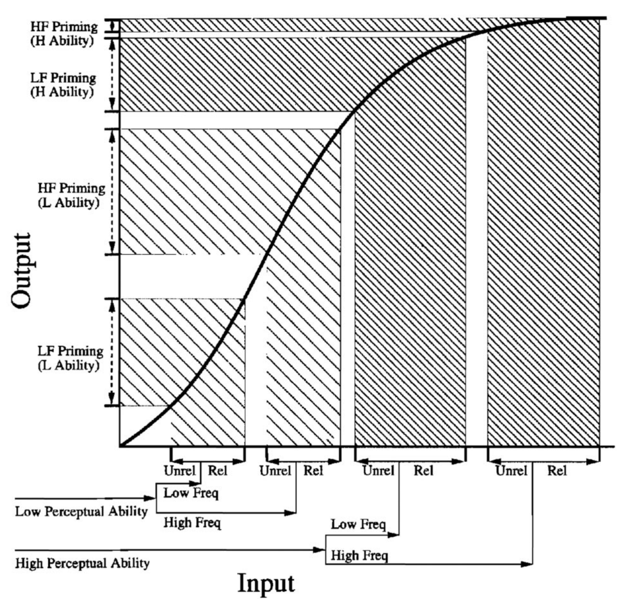

Figure 6. The sigmoid activation function of Plaut and Booth's (2000) model. HF = high-frequency; H = high; LF = low-frequency; L = low; Unrel = unrelated; Rel = related; Freq = frequency. Reproduced with permission from "Individual and Developmental Differences in Semantic Priming: Empirical and Computational Support for a Single-Mechanism Account of Lexical Processing," by D. C. Plaut and J. R. Booth, 2000, *Psychological Review, 107*, p. 832. Copyright 2000 by the American Psychological Association.

described could not handle nonword type effects (see p. 812 of their article), an earlier PDP model (Plaut, 1997) successfully simulated nonword type effects in isolated word recognition by implementing the assumption that more wordlike nonwords (such as pseudohomophones or TL nonwords) should be associated with higher stress values than less wordlike nonwords. However, it is noteworthy that the architectures of the two models are quite different. Specifically, Plaut's (1997) model, compared to its successor, had twice as many semantic units, had 10 times the number of hidden units, had six times the number of orthographic units, and was feedforward rather than recurrent (see Borowsky & Besner, 2006, for more details). Whether Plaut and Booth's model can indeed discriminate between words and wordlike nonwords accurately while at the same time correctly simulating the joint effects of nonword type, stimulus quality, frequency, and priming is an interesting empirical question that can only be appropriately addressed via simulations on the actual implemented model. Certainly, it will be challenging for the model to explain why manipulating the semantic stress of the nonword distracters exerts such different influences on semantic priming and word-frequency effects. Additionally, Borowsky and Besner (2006; Besner & Borowsky, 2006) have highlighted how the PDP model's reliance on a sigmoid function to relate input activation to RTs does not allow the model to simulate additive effects of two factors (i.e., nonword type and priming) when one of those factors (i.e., nonword type) produces an interaction with a third factor (i.e., word-frequency) within the same range of RTs (see also Plaut & Booth, 2006). A more recent study by Besner, Wartak, and Robidoux (2008) has also indicated that the model incorrectly simulates the joint effects of stimulus quality and word-frequency. Specifically, the model produces underadditivity, additivity, or overadditivity of the two factors depending on the size of the stimulus quality effect, whereas skilled readers yield a broader pattern of additivity.

Tying It All Together: The Case for a Multistage Model

The foregoing discussion makes it clear that even if one *only* considers mean-level RT performance, single-process models that postulate a common locus for frequency and priming effects will have difficulty explaining why (1) nonword type is additive with priming but interactive with frequency and (2) stimulus quality is additive with frequency but interactive with priming. McNamara (2005) has also pointed out that traditional priming accounts (e.g., spreading activation, verification, compound-cue) are too simple to capture the complex relations among word-frequency, stimulus quality, and semantic priming, and we have now added the differential effects of stimulus quality and nonword type on semantic priming to the mix (see Table 4).

As a starting point in this discussion, we are relying on Sternberg's (1969) additive factors logic to interpret the pattern of RT factor effects observed in the present study and to make inferences about the organization of the lexical processing architecture. The logic is based on the premise that independently changeable, serially arranged stages underlie lexical processing, and that processing is discrete (i.e., thresholded), that is, processing in a later stage begins only *after* processing in an earlier stage is complete. Additive effects of factors suggest that they influence different stages, whereas interactive effects suggest that they influence at least one common stage.

Because the current discussion relies on additive factors logic, it is important to remember there are some limitations. Specifically, it has been known for some time that although independent, separately modifiable stages imply additive effects, additive effects do not necessarily imply separate stages. For example, in the *cascade* model (Ashby, 1982; McClelland, 1979), all processes are operating continuously, and information is passed from one process to the next as soon it becomes available. Importantly, the cascade model, under some parameter constraints, is also able to produce approximately additive effects without a discrete-stage architecture. In order to better adjudicate between the two alternatives, Roberts and Sternberg (1993) examined the extent to which the stage and cascade models could account for human performance at the level of the mean RT and, more importantly, at the level of the RT distributions across different experiments (detection, identification, classification). Overall, they found that the predictions from the stage model provided a better fit to the empirical data sets. Interestingly, the cascade model was most successful under parameter settings where it resembled a stage model, although even this version of the cascade model was rejected after it made incorrect predictions about the relations among means and variances (Roberts & Sternberg, 1993; Sternberg, 1998). Related to this, Yap and Balota (2007) also observed

Table 4
Joint Effects of Stimulus Quality, Priming, Word-Frequency, and Nonword Type

Effect	Description of interaction (if applicable)	Study
1. Stimulus Quality × Priming × RP	Additive effects of Stimulus Quality and Priming when RP is low (.25). More priming for degraded, compared to clear, targets when RP is high (.50).	Stolz & Neely (1995)
2. Priming × Word-Frequency × Vocabulary	Additive effects of Priming and Word-Frequency for high-vocabulary participants. More priming for LF, compared to HF, targets for the low-vocabulary participants.	Yap et al. (2009)
3. Nonword Type × Word-Frequency	Larger word-frequency effects when more wordlike nonwords are used.	Stone & Van Orden (1993)
4. Additive effects of Stimulus Quality and Word-Frequency		Yap & Balota (2007)
5. Additive effects of Nonword Type and Priming		Lupker & Pexman (2010)

Note. RP = relatedness proportion; LF = low-frequency; HF = high-frequency.

additive effects of stimulus quality and word-frequency in means and in higher order moments (i.e., variance and skewness). This is a challenging pattern for the cascade model to handle, because it predicts additivity at the level of the mean but not necessarily at the level of higher order moments (Roberts & Sternberg, 1993). At a more general level, it is unclear how any model based on the interactive activation framework (which is predicated on top-down and bottom-up cascaded processing between modules) can handle the combined pattern of additive and interactive effects in the present study. For these reasons, and given the current level of development of computational models in the field, we believe that the stage framework continues to be a useful, albeit metaphorical, way for accommodating additive and interactive patterns of results from factorial designs.

Multistage Processing in Lexical Decision

In the remainder of this article, we describe how a multistage framework can provide an understanding of the intriguing qualitative differences between stimulus quality and nonword type effects, and between priming and word-frequency effects. To preview, our descriptive model is predicated on the idea that multiple stages of processing subserve lexical-semantic processing (Borowsky & Besner, 1993, 2006; Stolz & Besner, 1998). This allows the loci of priming and word-frequency effects to be further decoupled, along with an attempt to understand the clear differences in the underlying RT distributions as a function of these variables. Like Borowsky and Besner (1993), we do not make precise claims about the specific nature of the activation (i.e., discrete vs. continuous) across stages, but for ease of exposition, it is assumed that the model can contain both discrete and continuous processing features (see McNamara, 2005). Importantly, it has been shown that additive factors logic can be extended to cascaded processing frameworks or hybrid frameworks that include discrete and continuous features (McClelland, 1979, p. 312). Of course, we acknowledge that aspects of this model are speculative. However, as one reviewer has pointed out, it may take a while before word recognition researchers are able to develop a cogent, integrated account of the full range of extant data. In the meantime, we believe that a staged framework provides a useful way for organizing our findings and the attendant theorizing.

As a starting point, we adopt the multistage framework suggested by McNamara (2005) and Stolz and Besner (1998). According to this framework, there are three levels (letter, lexical, semantic) of representation and processing (see Figure 7); connections between different levels are excitatory, whereas connections within levels are inhibitory. Presenting a prime (e.g., NURSE) first activates letter-level representations, followed by activation at the lexical (via Pathway A) and semantic (via Pathway B) levels. Semantic priming is the result of spreading activation from the target word (i.e., NURSE) to related words (e.g., DOCTOR) within the semantic level. At the same time, activation is feeding backward from the semantic level to the lexical (via Pathway C) and letter (via Pathway D) levels, respectively preactivating the lexical-level and letter-level representations for DOCTOR. Hence, should DOCTOR appear shortly after NURSE, it can be processed more efficiently because its letter-, lexical-, and semantic-level representations have been partially activated. For our purposes, two additional points are worth highlighting. Based on the additive

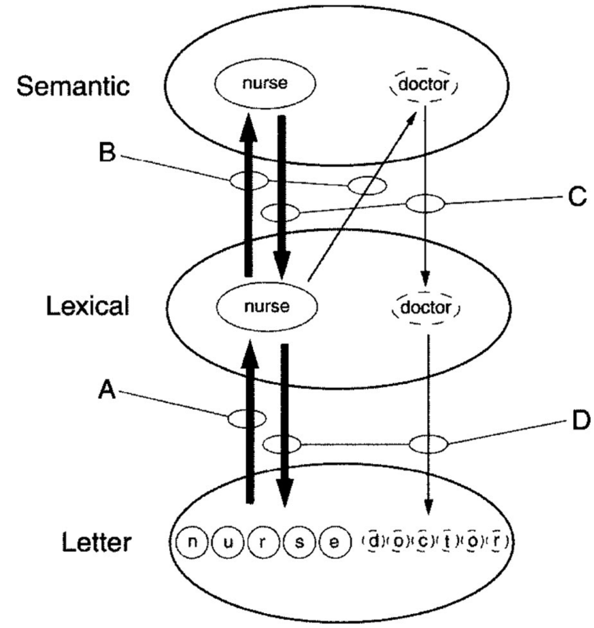

Figure 7. An interactive-activation multistage model of semantic priming. Reprinted with permission from *Semantic Priming: Perspectives From Memory and Word Recognition*, by T. P. McNamara, 2005, p. 41, New York, NY: Psychology Press. Copyright 2005 by the Taylor & Francis Group.

effects of stimulus quality and frequency (Yap & Balota, 2007) and the additive effects of priming and frequency for skilled lexical processors (Yap et al., 2009), it is assumed that stimulus quality influences only the letter level directly, word-frequency influences only the lexical level directly, and semantic priming influences only the semantic level directly. The framework also does not possess a dedicated mechanism for making lexical decisions. As we discuss in a later section, this omission has important implications.

How might this model account for extant effects, both at the level of mean RTs and at the level of RT distributional characteristics? First, consider the interaction between stimulus quality and priming, where priming effects are larger for degraded targets. The traditional account is as follows: Semantic priming reflects spreading activation within the semantic level and feedback to lower levels, which collectively preactivates the semantic, lexical, and letter-level representations of targets related to the prime. As a consequence of this feedback, related targets will be disrupted less by visual degradation than unrelated targets, yielding an overadditive interaction. Note that both spreading activation and semantic feedback are prospective in nature, because these processes occur before the target is presented. In other words, within the multistage framework, the received explanation for the Stimulus Quality × Priming interaction is based solely on prospective priming mechanisms. As discussed earlier, the recent study by Thomas et al. (2012) places further constraints on the mechanisms driving this interaction. Specifically, their findings clearly indicate that the Stimulus Quality × Priming interaction is mediated by a retrospective prime-retrieval mechanism that relies on backward target-to-prime associations. This mechanism is strategically engaged when target processing is difficult (e.g., when degraded or low-frequency words are presented), so that prime information can compensate for compromised bottom-up processing. Hence, instead of semantic feedback, the greater influence of priming for degraded targets might be better attributed to a retrospective prime retrieval process (e.g., retrospective semantic-matching; Neely & Keefe, 1989).

In this light, we can now revisit the interaction between stimulus quality and priming, where priming is reflected by distributional shifting for clear targets but increases across quantiles for degraded targets. When a prime is presented (e.g., NURSE), related representations in the semantic level[1] (e.g., DOCTOR) are preactivated through spreading activation, affording them a headstart on target processing. In this instance, the headstart yielded by the related prime is prospective in nature, because the facilitation occurs before the target is presented (e.g., Balota et al., 2008). However, when targets are difficult to resolve in some way (e.g., they are visually degraded), this engages a prime-retrieval mechanism (Thomas et al., 2012). The operation of this mechanism is reflected by both shifting and an increase in the slow tail of the distribution. Importantly, the influence of the prime is proportional to the difficulty of the trial, that is, priming effects are larger for slower (presumably more difficult) targets when they are degraded. Prime retrieval is a retrospective mechanism (e.g., Balota et al., 2008; Bodner & Masson, 1997; Neely et al., 1989; Ratcliff & McKoon, 1988) because it implicates processes after the target is presented.

The dichotomy between prospective (headstart) and retrospective (prime retrieval) priming is consistent with other empirical work. For example, Stolz and Neely (1995) demonstrated that the Stimulus Quality × Priming interaction was present only when relatedness proportion (RP; i.e., the proportion of word targets preceded by a related prime) was high (e.g., 0.50). When relatedness proportion was decreased (e.g., 0.25), the two variables produced additive effects. In other words, retrospective prime retrieval, which the Stimulus Quality × Priming interaction is a marker for, occurs only in the high RP condition (i.e., when the utility of a related prime is high). Related to this, Yap et al. (2009) reported that the Frequency × Priming interaction was observed only in participants with relatively lower levels of vocabulary knowledge. Participants with more vocabulary knowledge produced additive effects of the two factors. This fits well with the aforementioned proposal that there is retrospective prime retrieval only when the utility of related prime information is high. Specifically, prime retrieval is not evident for higher-vocabulary-knowledge participants because the utility of the prime is relatively low for such participants who, by virtue of possessing high-integrity lexical representations (e.g., Perfetti & Hart, 2002), are able to process both high- and low-frequency targets fluently. In summary, the RT distributional results of the Priming × Stimulus Quality interaction are consistent with the notion that there is retrospective prime retrieval when target processing is effortful and the utility of the prime is high (see Thomas et al., 2012, for further discussion of prospective and retrospective priming effects).

We believe the multistage framework proposed above can also be extended in a relatively straightforward manner to accommodate the additive effects of nonword type and priming. As discussed earlier, the Nonword Type × Word-Frequency interaction, in conjunction with the additive effects of nonword type and priming, *cannot* be reconciled with the premise that nonword type, word-frequency, and semantic priming affect the same, lexically-driven mechanism (Lupker & Pexman, 2010). Instead, one needs to posit additional processes/mechanisms, which are more tuned to the task-specific decision mechanisms in the lexical decision task. Specifically, while a primary set of lexical processes is sensitive to frequency and priming (but not to nonword type), a secondary process is influenced by frequency and nonword type (but not by priming). In this light, we suggest augmenting the multistage framework with an additional word/nonword discrimination mechanism that operates *after* the semantic level. Indeed, incorporating such a decision-making stage is compatible with the idea that in lexical decision, experimental variables (e.g., word-frequency) can influence both lexical processing *and* postlexical decision-making mechanisms that are specific to the task (Balota & Chumbley, 1984). For example, the decision stage could be modeled after familiarity-based accounts (e.g., Balota & Chumbley, 1984; Besner, 1983; Besner & Swan, 1982), which have been useful for explaining nonword type effects (e.g., Yap et al., 2006) and other lexical decision phenomena.

Familiarity-based accounts strongly emphasize the role of any information that can be recruited by participants to discriminate between words and nonwords. Because words are more familiar and meaningful than nonwords, familiarity[2] (and any variable correlated with familiarity) is a useful dimension for driving the discrimination process. For example, frequency influences the postlexical discrimination process because low-frequency words, compared to high-frequency words, are more similar to nonwords on the relevant familiarity/meaningfulness dimension. Because of the increased overlap between low-frequency words and nonwords, participants may be compelled to engage in more attention-demanding analyses (e.g., spell-checking or retrieving semantic referent) for such words, hence slowing lexical decision latencies (Balota & Spieler, 1999). Clearly, in the context of very wordlike nonwords that include a transposed pair of letters, it would be adaptive for the decision maker to conduct a check process to ensure that the spelling is correct.

Alternatively, the postlexical decision stage might be represented by a diffusion-based process (Ratcliff et al., 2004), which is able to account for correct and error RTs very well, both at the level of the mean and at the level of their distributions. Specifically, during target processing, the system is monitoring any activity that is relevant for discriminating between words and nonwords, and this activity could map on to a *wordness* value (i.e., a familiarity-like metric that reflects how wordlike a stimulus is) that drives drift rates in a noisy diffusion decision process (Plaut, 1997; Ratcliff et al., 2004). In order to accommodate nonword type effects, the mapping between semantic activity and drift rate could be differentially weighted depending on the extent of overlap between words and nonword distracters (see Yap et al., 2006, for

[1] Although we are suggesting that semantic priming truly resides in the semantic memory system, there is evidence that the priming effect may indeed be due to associative co-occurrence and, hence, resides within the lexical network (see review by Hutchison, 2003).

[2] Here, familiarity refers to a multidimensional quantity that reflects the orthographic and phonological similarity of a letter string to real words.

more discussion). Of course, without explicit modeling of the full set of effects, there is no assurance that a hybrid model that integrates multiple stages with a diffusion mechanism can faithfully approximate performance.

To recapitulate, the additive effects of nonword type and priming are consistent with the notion that nonword type, but not priming, influences postlexical decision-making mechanisms that are sensitive to familiarity or wordness. Of course, this predicts that variables that contribute to the familiarity/wordness of a letter string should interact with nonword type. The canonical example is word-frequency, that is, high-frequency words are perceived as more familiar than low-frequency words. Other variables that could potentially increase familiarity/wordness include imageability (Cortese & Fugett, 2004), age of acquisition (Cortese & Khanna, 2007; Juhasz, 2005), number of senses (Pexman & Lupker, 1999), number of associates (i.e., number of distinct first associates elicited in a free association task; Duñabeitia, Avilés, & Carreiras, 2008), number of features (Pexman, Lupker, & Hino, 2002), body-object interaction (i.e., the extent to which referents can be physically interacted with; Siakaluk, Pexman, Aguilera, Owen, & Sears, 2008), sensory experience rating (i.e., the extent to which a word evokes sensory/perceptual experiences; Juhasz, Yap, Dicke, Taylor, & Gullick, 2011), and repetition (Balota & Spieler, 1999). With this in mind, it is noteworthy that nonword type has already been shown to interact with frequency (Stone & Van Orden, 1993), imageability (James, 1975), number of senses (Pexman & Lupker, 1999), and number of features (Pexman et al., 2002), with the other variables yet to be investigated. Of course, the corollary here is that priming a word with its semantic associate does *not* increase its familiarity/wordness.

Why does semantic priming *not* increase the familiarity or wordness of a word? The repetition priming (i.e., primes are identical to the target) literature might be informative here. Although the precise bases of repetition priming remain controversial (see Tenpenny, 1995, for a review), most researchers agree that repetition effects involve multiple mechanisms, that is, a short-term effect reflecting lexical activation and a long-term effect reflecting memory trace retrieval (see Coane & Balota, 2011; Versace & Nevers, 2003). Interestingly, Forster and Davis (1984) have suggested that the locus of repetition priming's episodic influence, but not its short-term lexical effect, is at the decision stage of the lexical decision task. We have proposed that in the absence of retrospective prime retrieval, which appears to be modulated by the utility of the prime, semantic priming effects reflect a simple headstart mechanism, wherein primes preactivate related targets to the same extent. Parenthetically, the notion of a headstart converges nicely with the observation that the semantic priming of clear targets reflects changes in nondecision (i.e., encoding and response execution) time but not drift rate.

Assuming that these preactivated targets do not lay down episodic traces, and priming-based familiarity/wordness critically depends on episodic influences, it therefore follows that headstart-mediated semantic priming should produce additive effects with any variable (e.g., nonword type) whose influence is localized to the decision stage. Indeed, the notion that semantic and repetition priming tap different processes meshes well with den Heyer and Goring's (1985) finding that the effects of semantic and repetition priming are additive in lexical decision. Of course, it is important to emphasize that this explanation is *post hoc* and needs to be empirically verified in future studies.

Conclusions

In summary, semantic priming is one of the most robust and extensively studied effects in the word recognition literature. Using both conventional analyses of means and converging analyses (ex-Gaussian, quantile, diffusion modeling) of RT distributions, the present study provides a clearer understanding of the intriguing dissociation between semantic priming and different variables that increase the difficulty of the lexical decision task. Specifically, semantic priming produces interactive effects with stimulus quality (primarily in the tail of the RT distribution) and additive effects with nonword difficulty. In contrast, word-frequency produces the opposite pattern of joint effects, that is, word-frequency produces additive effects with stimulus quality, and interacts with nonword difficulty, again primarily in the tail of the distribution (see Yap et al., 2006). We are led to a descriptive framework that relies on distinct and interactive stages of processing leading from input to decision in the lexical decision task.

Of course, the present account is based on a metaphorical description of the stages and processes that we and others (e.g., Borowsky & Besner, 1993; McNamara, 2005; Stolz & Besner, 1998) believe are useful for explaining the complex set of results that have now been well-established in the rich visual word recognition literature. We have not endorsed a particular computational approach in accommodating the present set of results, because it is likely that while extant models may capture a subset of findings, other findings may fall outside the scope of a given model. Indeed, these latter findings may reflect specific stages of processing brought on-line by the demands of the lexical decision task. We look forward to further explorations of these intriguing results within extant models.

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(*Appendix follows*)

Appendix

Stimuli in Experiments 1 and 2

PRIME	TARGET	PRIME	TARGET	PRIME	TARGET
MINDED	ABSENT	BIT	DRILL	HALLOWEEN	PUMPKIN
MISTREAT	ABUSE	HUMILIATE	EMBARRASS	VIOLET	PURPLE
SUGGESTION	ADVISE	HUG	EMBRACE	FURY	RAGE
PHYSIOLOGY	ANATOMY	JEALOUSY	ENVY	ACCEPT	REJECT
RENOUNCE	ANNOUNCE	DIMINISH	FADE	BEEF	ROAST
AGGRAVATE	ANNOY	PHYSICAL	FITNESS	DECAY	ROT
BLUEPRINT	ARCHITECT	PASTE	GLUE	SPOILED	ROTTEN
DESCEND	ASCEND	GANDER	GOOSE	SELLER	SALESMAN
AMAZE	AWE	PASTURE	GRAZE	UPSTREAM	SALMON
TUTU	BALLET	CHARCOAL	GRILL	SUB	SANDWICH
ROUGE	BLUSH	NAIL	HAMMER	REPRIMAND	SCOLD
COMPUTE	CALCULATE	CROPS	HARVEST	EGGS	SCRAMBLE
DIAGRAM	CHART	HITCH	HIKE	WALRUS	SEAL
GOURMET	CHEF	CLUE	HINT	GROW	SHRINK
MONKEY	CHIMPANZEE	HOSTESS	HOST	DRAW	SKETCH
CHOIR	CHORUS	NOTIFY	INFORM	SLOPE	SKI
VACUUM	CLEANER	WOODWIND	INSTRUMENT	TECHNIQUE	SKILL
CASHIER	CLERK	OFFEND	INSULT	SLENDER	SLIM
MIX	COMBINE	CREATE	INVENT	SUFFOCATE	SMOTHER
FUSS	COMPLAIN	RUN	JOG	DOZE	SNOOZE
UNDERSTAND	COMPREHEND	POUCH	KANGAROO	MASSAGE	SOOTHE
LINK	CONNECT	OZONE	LAYER	REAP	SOW
ARTS	CRAFTS	SERMON	LECTURE	ROT	SPOIL
IMAGINATION	CREATIVITY	CHAIN	LINK	DETECTIVE	SPY
KNIT	CROCHET	FLUID	LIQUID	POSTAGE	STAMP
BETRAY	DECEIVE	FORTUNE	LOTTERY	PILOT	STEWARDESS
INCREASE	DECREASE	BUTLER	MAID	ADD	SUBTRACT
VICTORY	DEFEAT	TUPPERWARE	MICROWAVE	SCALPEL	SURGEON
THAW	DEFROST	PLUS	MINUS	BROOM	SWEEP
REPUBLICAN	DEMOCRAT	DIVIDE	MULTIPLY	LIGHTNING	THUNDER
VARY	DIFFER	ARTIST	PAINTER	NEAT	TIDY
INVENT	DISCOVER	PINK	PANTHER	FLOOR	TILE
DISGRACE	DISGUST	GUARDIAN	PARENT	UNDERGROUND	TUNNEL
HONEST	DISHONEST	HESITATE	PAUSE	SWEEP	VACUUM
LIKE	DISLIKE	ALLOW	PERMIT	HERO	VILLAIN
DISINTEGRATE	DISSOLVE	WORD	PHRASE	SERVER	WAITER
SWIMMER	DIVER	ELECTRICIAN	PLUMBER	WAITER	WAITRESS
MULTIPLY	DIVIDE	OUNCE	POUND	BLUBBER	WHALE
FLIPPER	DOLPHIN	RECOGNITION	PRAISE	EVIL	WICKED
MULE	DONKEY	COPIER	PRINTER	LENGTH	WIDTH

(*Appendix continues*)

Appendix (*continued*)

PRIME	LEGAL NW	PRIME	LEGAL NW	PRIME	LEGAL NW
SCALDED	ABBLAIMS	ANGER	FOLT	DATA	PRINGS
MERELY	ABLOW	PIN	FRUNKER	EXPANSION	PROWN
SATISFIED	ABTRAY	PRIVACY	GAISE	RISKY	PRUEAL
ADHESIVE	AIG	REEF	GIRES	LUNGS	PUDGET
EXERCISE	ALVEOBA	PUNK	GLERVING	ZEBRA	RACUST
REFRAIN	ASTITE	VESSEL	GLIP	PANCAKE	ROG
POLLS	ATTOND	TOUGHEN	GRASH	REMARKABLE	SCHINTER
PIPE	ATTOW	GLORIOUS	HANDID	SCALP	SCOVENANCE
SNIP	BAGGOT	DETOUR	HIFE	FOLDING	SCRASH
MOBSTER	BANDOD	CURE	HOAL	AMPLE	SETRAYS
HORRORS	BEEHOVE	BRIDE	HUPS	COMEDY	SHUMP
GENTLE	BLIFFER	ZERO	INTRALECTS	SHADOW	SILD
CLINIC	BLOWNINGLY	POODLE	IRRITERACY	DECK	SLONK
RESENTFUL	BLUPID	CREWS	JOP	HELICOPTER	SLOUND
NUT	BROWERING	BILLION	LANDIT	LABELS	SLOUP
INDIVIDUAL	BRUNK	TOY	LARGIN	PORTION	SMASTOR
SHOWN	CARNAY	DIM	LER	PRYING	SMICKER
MELLOW	CERSERK	LAD	LICKET	GOAL	SNI
FORK	CHIGS	AMBITION	LICYCLE	DWELLING	SNILL
MYSTERIOUS	CHIRM	INVENTORY	LIDEN	TALENTS	SONE
CHEAPER	CHRUTTER	CIVILIZED	LINTER	SPENDS	SPOVE
DEEPER	CHUGGLE	SQUANDER	MENCHES	STEW	STECIPICE
FESTIVAL	CLANSFER	IDLE	MIFER	KICKING	STORIFIED
COUNTRIES	CLEB	TIMING	MOIL	QUANTITY	SUSHER
FLASHBACK	CLERMOS	JIGSAW	MOT	TANKER	SUTTRESS
SPRINKLE	CLIRMISHES	MOTION	MURDINESS	GARBLED	TACE
CRUSHED	DALTOP	LINING	MURGLARY	INCENSE	TAULDRON
TONE	DEPATE	FROZE	NALLOW	COMMERCIAL	THILING
TECHNOLOGY	DETROTH	INVITATION	NOTARUSE	SINGLED	THRIP
TILTED	DILT	ALIENS	OPPASION	CEREAL	TRAVELAN
THEREIN	DORST	SUSPICIOUS	PACKLES	LION	TRINACH
ALTO	DRALLER	QUOTA	PAULT	DRIVEWAY	TROKER
HANDING	DRAMENS	ANGLE	PHRAWL	OILY	TROOGE
EARN	DRATTY	CHAT	PLARTLY	ROB	TROST
GOSSIPING	DRELL	SPADE	PLAUGABLE	SOBS	TUAL
REDUCE	DROCKER	CLUSTER	PLIGOTS	MASS	TULL
TRANSPORT	ESIN	FOREHEAD	PLINDED	SCARF	UNLUND
RUB	FERBS	POSED	PLURIOUS	FLOURISH	VORGAL
OPTIMISTIC	FIGHTEN	SOAP	PRAKES	SONS	WALPS
BANQUET	FLINDLE	LIDS	PRANKFUL	WALTZ	WOCKED

(*Appendix continues*)

Appendix (*continued*)

PRIME	TL NW	PRIME	TL NW	PRIME	TL NW
SQUANDER	ABN	AMBITION	DISCNONECT	ALIENS	PORM
INVENTORY	ADMINSITER	CHEAPER	DUTSY	CEREAL	POVRETY
TALENTS	ADVSIOR	KICKING	EANREST	REEF	PULBISH
SCALDED	ALD	CREWS	ELETCRIC	FORK	QEUER
SPADE	AMSUE	LIDS	ELPOE	CURE	QUATNITY
NUT	AUMSE	LAD	ETIQEUTTE	IDLE	REA
CLUSTER	BAGDE	RISKY	EXPNAD	PRYING	RECEPIT
REMARKABLE	BAKSET	COMMERCIAL	FAIERST	GOAL	RESREVE
HORRORS	BANR	POSED	FECTH	DATA	RIBOBN
DRIVEWAY	BASBEALL	FLASHBACK	FLWOER	SUSPICIOUS	RUOMR
ALTO	BEAHLF	RUB	FOERST	MOBSTER	SAOP
GENTLE	BLAEK	SHADOW	FOOELD	ZEBRA	SAPMLE
OILY	BLESSNIG	GLORIOUS	FRAMGENT	DIM	SARACSTIC
SPENDS	BLIDNED	FOLDING	GIGNER	FOREHEAD	SATLL
CIVILIZED	BOBMS	SNIP	GIRP	LINING	SCAK
MASS	BOUELVARD	SATISFIED	GMY	COUNTRIES	SHERWD
SOBS	BREAHTER	COMEDY	GRUGDE	DETOUR	SHOLEACE
PORTION	BUGIGNG	THEREIN	HOKCEY	PUNK	SLUBMER
SCALP	CASAUL	GARBLED	HOTSILE	STEW	SPATSIC
DWELLING	CATROON	HELICOPTER	HUDRLE	POODLE	SPLEDNID
SONS	CELLOHPANE	FLOURISH	INGREDEINT	MELLOW	SPRAK
QUANTITY	CHAIROT	MERELY	IRM	MOTION	STIE
PRIVACY	CHEIMST	EXPANSION	JEKRED	BANQUET	STRATLE
AMPLE	CHEKES	LUNGS	LANUCH	QUOTA	SUACE
OPTIMISTIC	CHIARS	ADHESIVE	LAOF	ZERO	SUCECEDS
JIGSAW	CILP	INCENSE	LEAHTER	PIPE	SUOR
ANGER	CLIAMTE	REDUCE	LOACTE	INDIVIDUAL	SVAES
SINGLED	CONENCT	CRUSHED	LODULY	FESTIVAL	SWRON
LION	COPMASS	SOAP	LOGDE	TIMING	SYL
VESSEL	COUSNEL	CHAT	LSATS	CLINIC	TAEKR
BRIDE	CRITREIA	MYSTERIOUS	LYIRC	PANCAKE	TEPMER
FROZE	CRON	BILLION	MAITNAIN	ROB	THRETAEN
ANGLE	CUHCK	TECHNOLOGY	MAKRED	TANKER	TIDNIGS
SHOWN	DAERD	LABELS	MASSGAE	TRANSPORT	TRGAIC
TILTED	DEABTE	POLLS	MCOK	TOUGHEN	VANQIUSH
GOSSIPING	DEDALY	REFRAIN	MNEU	INVITATION	VIAN
SPRINKLE	DEINAL	EXERCISE	MZAE	DECK	VITRUE
SCARF	DETETNION	RESENTFUL	OWEND	TONE	WAETRS
TOY	DETREMINE	PIN	PAESANT	DEEPER	WIERD
WALTZ	DISCILPINE	HANDING	PEIRSH	EARN	WOVLES

Note. NW = nonword; TL = transposed-letter.

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