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Evaluating Theories of Bilingual Language Control Using Computational Models

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by

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DEDICATION

I dedicate this dissertation to my family. To my wife, Olya, I love you. Thank you for being my rock. You were always there to support me and to lift me up. You always listen. You always care. Without you, I doubt I would have completed my degree. To my sons James and Alex, I love you. You are wonderful. Both of you have grown up so much. You two helped give me the strength to persevere. To my parents Deborah and Dean Lowry, I love you. Your encouragement was instrumental. You taught me the value of hard work and integrity. I am grateful that we could visit so much. Olya, James, Alex and I love going to "grandma and grandpa's house" to play, relax and unwind. To my siblings Lynne, Dianne, Ray, Suzanne, Jeff, Katherine and Steven, I love you. Thank you for babysitting. Thank you all for everything.

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ABSTRACT

Bilingual language control refers to how bilinguals are able to speak exclusively in one language without the unintended language intruding. Two prominent verbal theories of bilingual language control have been proposed by researchers: the inhibitory control model (ICM) and the lexical selection mechanism model (LSM). The ICM posits that domain-general inhibition is employed in order to suppress the unintended language's activation. The LSM posits that inhibition is not used; rather a lexical selection mechanism targets only the intended language's words. In order to better test the theories' hypotheses, I developed computational models to estimate participants' reaction times when naming in blocks of semantically related pictures and in blocks of semantically unrelated pictures. For these tasks, the ICM model predicts that semantic interference will be abolished when bilinguals switch languages, while the LSM model does not. In Experiment One, English-Spanish bilinguals named pictures that were either semantically related to the previous four trials, or semantically unrelated to the previous four trials. Research indicated that language switching did not abolish priming effects, supporting the ICM. These results contradict conclusions found in previous literature. To reconcile this, another experiment was conducted. It was similar to Experiment One, except filler trials separated semantically related trials. Results showed that each time a semantically related neighbor was presented, naming latency increased by ~10ms regardless of language switching or number of filler items. It suggests that the existing literature mistook incremental learning effects as priming effects, and it demonstrates a need to incorporate theories of incremental learning into theories of bilingual language control.

CHAPTER ONE:

INTRODUCTION

When bilinguals speak, they must choose their words carefully. Depending on the audience, a bilingual may be free to choose words from either language (e.g., when conversing with other bilinguals), or they may be constrained to only one language (e.g., when conversing with monolinguals). It is not well understood how bilinguals keep from speaking in their dominant language (L1) when exclusively speaking in their weaker language (L2). The goal of this dissertation is to address this question by comparing two prominent verbal theories of bilingual language control in speech production (the Inhibitory Control Model and the Lexical Selection Model; referred to as the ICM and LSM respectively) and their predictions regarding semantically related stimuli. The core difference between the two theories is the mechanism used to control bilingual language production: the ICM posits that inhibition is needed to suppress the non-target language, whereas the LSM posits that a non-inhibitory mechanism is used. This leads to two different predictions related to priming effects. When naming a block of semantically related pictures, the LSM predicts that competition between semantic neighbors keeps increasing even after participants switch languages. On the other hand, the ICM proposes that competition between semantic neighbors is reduced after a language switch.

The dissertation consists of three studies. The first uses simulations to make specific predictions for each theory about how spreading activation affects naming latencies after a language switch. This was tested via their instantiation in computational models. The second experimentally tests those predictions, and the third (also an experiment) helps clarify previous research that may have misinterpreted results due to the experimental paradigm used. Results from these three studies demonstrate that (1) the ICM and LSM computationally predict that within-language spreading activation creates interference from one trial to the next, (2) only the ICM computationally predicts an abolition of those interference effects after a language switch, (3) spreading activation effects are abolished after a language switch (Experiment One), supporting the ICM , (4) contrary to the predictions of both theories, spreading activation leads to within-language facilitation from one trial to the next and (5) cumulative semantic interference appears to be the result of a learning mechanism, which is beyond the reach of current models of bilingual language control. Therefore, an analysis of cumulative semantic interference does not test how switching languages affects spreading activation.

In light of these results, I suggest that future models of bilingual language control need to incorporate the following ideas. First, inhibition is indeed used to control language output (as the ICM suggests). Second, incremental learning also affects bilingual speech production, but it is largely unaffected by language switching. Third, within-language word production is non-competitive in nature.

The rest of this introduction will briefly focus on important aspects of speech production needed to understand the ICM and LSM. First, I discuss the steps involved in monolingual and bilingual models of word production and how activation flows from one step to the next. Second, I examine the nature of competition, both between and within languages.

Steps Involved in Language Production

Monolingual and bilingual models tend to agree that lexical access of single words involves at least two stages. First, the word is retrieved from memory. Then its sounds are planned (i.e., phonological encoding; see Bock & Levelt, 2002; Brown & McNeill, 1966; Costa & Caramazza, 1999; Dell, 1986; Dell & O'Seaghdha, 1992; Dell, Chang, & Griffin, 1999; Green & Abutalebi, 2013 ; Levelt, Roelofs, & Meyer, 1999; Levelt, 1992; Roelofs, 1992, 1997; Vigliocco, Antonini & Garrett, 1997). The LSM and ICM focus mainly on lemma retrieval and the competition (or lack thereof) that happens between words. A lemma is a combination of semantic and syntactic information related to a word, but it does not contain information about a word's phonology. The models do not specify whether competition exists at the phonological level or whether lemma retrieval must be complete before phonological encoding can begin. Because of this, the rest of this dissertation emphasizes issues involved in selecting lemmas from memory, and I will use the term word to denote lemma.

Most monolingual theories of word production assume that words and concepts are stored separately in the brain. If true, there has to be some connection between the semantic network and lexical network[1] (see Dell, Chang, & Griffin, 1999; Harley, 1993; Levelt, Roelofs, & Meyer, 1999; Oppenheim, Dell, & Schwartz, 2010; Roelofs, 1992). For example, the word *bird* might be linked to features within the semantic network like *has wings* and *flies*. Intending to say bird activates those features within the semantic network. Since those features are also connected to similar words (e.g., *eagle, bat*; i.e., semantic neighbors), they also get activated to some degree. In this way, activation from the semantic network flows to several related words (Collins & Loftus, 1975).

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[1] Some models are decompositional – meaning words are linked to several features. Others are non-decompositional – meaning words are linked to whole concepts. This distinction is not made by either the LSM or ICM.

Both the ICM and LSM assume that there is only one conceptual network, which is linked to words in both languages. They also assume that activation can flow from the semantic network to both L1 and L2 lexicons at the same time (see Colomé, 2001, and Hermans, Bongaerts, De Bot, & Schreuder, 1998, for experimental evidence supporting this conclusion; for a review see Kroll, Bobb, & Wodniecka, 2006). This would appear to make choosing the intended word more complicated for a bilingual. Not only are semantic neighbors potential targets of lexical selection, but interlingual synonyms (i.e., a word's translation) are too. For this reason, researchers have suggested that bilinguals need an additional mechanism that constrains output to only one language.

An important reason that bilinguals might need an additional mechanism to constrain output is because it is generally assumed that L1 words are more strongly connected to the semantic network than L2 words are (this assumption is based on work by Kroll & Stewart, 1994, and Kroll, Van Hell, Tokowicz, & Green, 2010). This allows activation to flow more strongly to L1 words than to L2 words. The ICM assumes that inhibition is the mechanism needed for constraining output. When bilinguals speak in their non-dominate language (i.e., L2), they suppress activation in their dominant language (i.e., L1). The LSM, on the other hand, assumes a non-inhibitory mechanism is used. These mechanisms are discussed more in-depth in chapter two.

Competition Among Words – Between and Within Languages

There are two views within the monolingual literature regarding competition during speech production. The first is that lexical entries compete for selection, and the second is that lexical entries do not compete. It should be noted that most monolingual and bilingual models assume some form of competition. Both the LSM and ICM assume that, within a language, words compete for selection (e.g., the English word *dog* competes with the English word *cat*). How quickly a word can be selected depends on how much activation it receives from the semantic network compared to how much other words receive. If a target word is highly active, and its semantic neighbors are not, then naming should be relatively fast. However, only the ICM proposes that this type of competition happens between languages (e.g., the English word *dog* competes with the Spanish word *gato,* meaning *cat* in English). This difference is important in understanding how the ICM and LSM resolve activation of the unintended language, and it is critical in setting up predictions. Therefore, I will deal with the topic of competition in more detail than the others.

The traditional view is that lexical entries compete with each other. If choosing the correct word (e.g., *dog*) depends on the degree to which its activation level is greater than its semantic neighbors, then a highly active semantic neighbor (e.g., *cat*) may make it more difficult to select the correct lexical entry. Studies that find semantic interference in picture-word paradigms support this idea (e.g., Damian & Bowers, 2003; Hermans 1998; Meyers, 1996; Roelofs, 1992; Schriefers et al., 1990). Under this paradigm, participants have to name pictures while a distractor word is presented orally or visually. When the distractor (e.g., *cat*) is semantically similar to the target (e.g., *dog*), naming slows down compared to when the distractor (e.g., *airplane*) is less semantically related to the target. This increase in naming latency has been attributed to competition between lexical entries at the time that a word in the lexicon has to be selected, and it is known in the literature as *semantic interference*.

The problem with distractor tasks like the one just described is that they may increase the activation of a semantic neighbor in a way that slows naming, but such slowing may not be attributable to competition within the lexicon. One might argue that as a participant is about to say the target word, the distractor's activation gets primed by it being presented visually during a trial. This results in the distractor getting temporarily selected, but it is not produced due to some internal monitoring mechanism that prevents articulation (see Hartsuiker & Kolk, 2001). The time it takes for the monitor to reject the distractor is added to the total time it takes to name the target. Because of this, two other paradigms have been used to test for semantic interference: the cyclical paradigm, which elicits *cumulative semantic interference* (CSI), and the blocked naming paradigm.

Usually under the cyclical paradigm, participants name pictures that come from various semantically-related categories. To participants, the pictures seem like they are randomly presented: pictures on trials n and n-1 are not from the same category. Rather, words from a given category may be separated by several filler trials[2]. Naming latencies for semantically-related trials tend to be slower than naming latencies in unrelated trials[3] (e.g., Damian & Als, 2005). Additionally, each time a picture from the same semantic category is presented, naming latencies increase by 10-30ms compared to the previous semantically-related trial, regardless of how many filler trials there were separating them (i.e., semantically-related trials; see Howard, Nickels, Coltheart, & Cole-Virtue, 2006; Navarrete, Del Prato, & Mahon, 2012; Navarrete, Mahon, & Caramazza, 2010). CSI results seem to indicate that activation builds up between semantic neighbors in the lexical network, creating increasing competition.

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[2] Filler trials are not included in analyses of response times. Additionally, in some experiments words from one semantic category may be used as fillers for other semantic categories.

[3] In categorization and comprehension tasks of categorically related stimuli, facilitation is usually observed. One explanation for this difference is given by Kroll and Stewart (1994). They found categorical interference in picture naming, but facilitation when recalling picture names. They suggest that picture naming requires a deeper level of processing than other tasks such as recall (or lexical decision). Competition happens at this deeper level, which creates interference.

There is a theoretical problem when examining results of the cyclical paradigm. Competition-based models, such as the ICM, have trouble explaining how naming latencies increase between semantically-related words even when those words are separated temporally by several filler trials. Competition is thought to arise from spreading activation within the semantic network which, in turn, activates several words within the lexicon. Theoretically, spreading activation within the semantic network is short-lived and should decay quickly (see Navarrete, Prato, Peressotti, & Mahon, 2014). Activation within the lexicon should also decay in the same manner. For this reason, it has been suggested that CSI from cyclical paradigms is a result of incremental learning and not the increase of activation within the lexicon (see Navarrete, Del Prato, & Mahon, 2012; Navarrete, Mahon, & Caramazza, 2010; Navarrete, Prato, Peressotti, & Mahon, 2014). Incremental learning is an idea inspired by neural network models (e.g., Oppenheim, 2010) that try to understand how an organism is able to continually adjust to its environment. It is proposed that such learning happens even in picture naming studies. When a picture is presented (e.g., *dog*), and a participant names it, the neural connections between the concept and word become strengthened. This strengthening is long lasting, and is different than just temporary activation. When the picture is presented a second time later on in an experiment, the word is retrieved more quickly. This type of facilitation is termed *repetition priming.*

There is a cost associated with incremental learning. When a picture is presented, the connections between the target word and the semantic network get stronger, but the tradeoff is that the connections between semantically-related neighbors and the semantic network become weaker. For example, naming a picture of a *bat* will strenghten *bat's* conceptual nodes to its lexical nodes, but it will weaken *whale's* connections to the conceptual nodes that are shared with *bat*. When *whale* must be named, it takes longer to retrieve it from the lexicon. However, at the end of the trial, *whale's* connections are strengthened, and its neighbors' are further weakened. When a third neighbor (e.g., *dog*) gets named, naming takes even longer than it did for *whale*. See Figure 1 for a diagram of how incremental learning is theorized to work in a naming experiment.

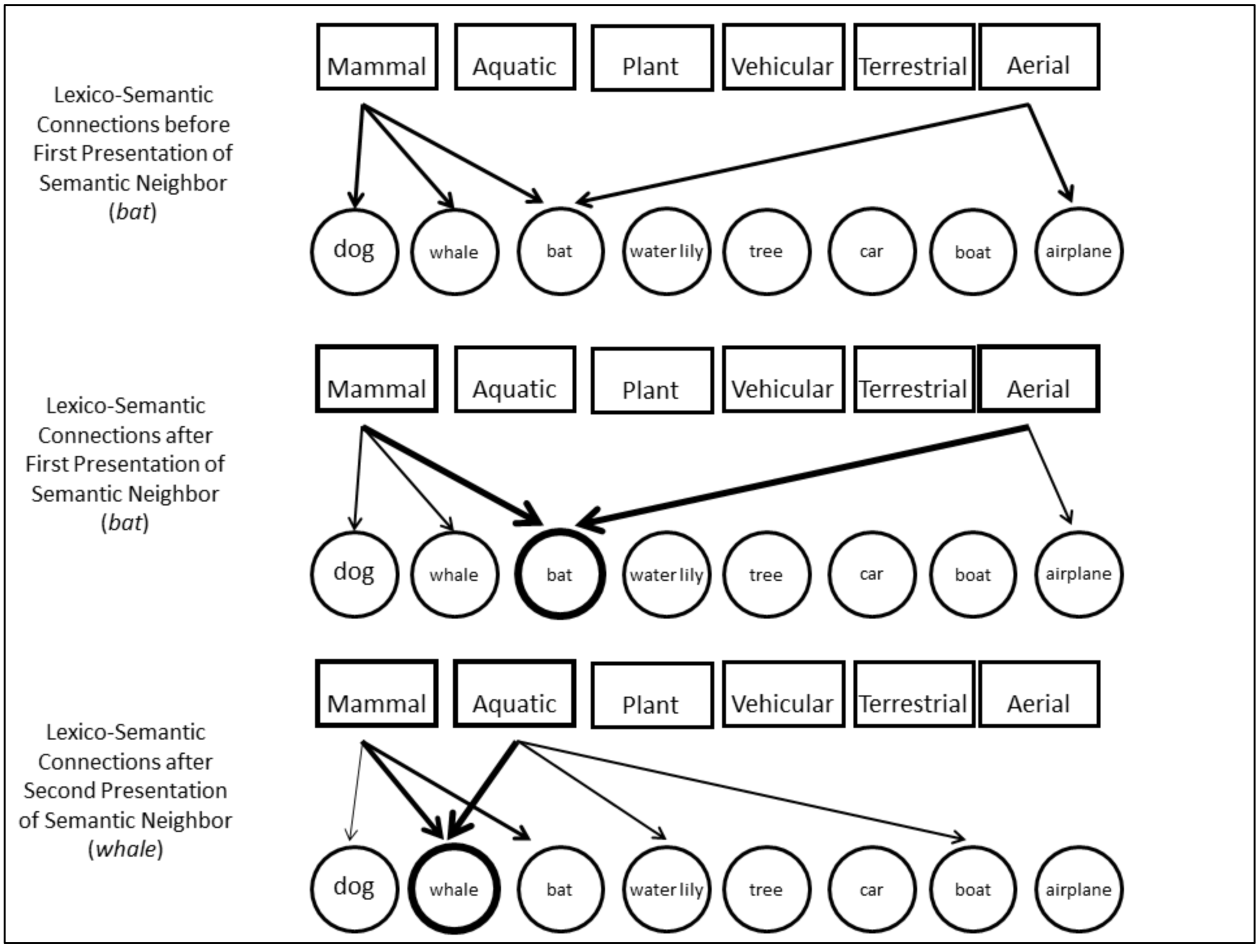


Figure 1. A diagram of how incremental learning in a naming task works, adapted from Oppenheim et al., (2010). Squares represent semantic features, circles represent words in the lexicon and arrows represent connections between the two. The thicker the arrow, the stronger the connection is.

Because the cyclical paradigm may lead to incremental learning effects and not spreading activation effects, the blocked naming paradigm may be a better method for manipulating within-language competition by spreading activation. Under the blocked naming paradigm, participants name pictures (or read words) in semantically-related or unrelated blocks. Unlike the cyclical paradigm, there are no filler items that separate semantically-related stimuli. Spreading activation from naming a semantic neighbor on one trial has less time to decay before naming starts on the next trial. When averaging across blocks, naming latencies tend to be slower for semantically-related blocks than for unrelated blocks (e.g., Damian & Als, 2005; Kroll & Stewart, 1994; Navarrete et al., 2014). Blocked naming studies support the initial inferences drawn from distractor tasks and cyclical tasks: semantically-related items seem to compete with one another for output. This makes the blocked naming paradigm a better method theoretically to manipulate within- and between-language competition.

However, an important question remains: *Does the blocked naming paradigm by itself fully remove the potential incremental learning confound?* If average naming latency is calculated by block, it most likely does not fully remove the confound. Specifically, each time a word is repeated within an unrelated block, it is affected only by *repetition priming* (e.g., *dog's* connections to the semantic network strengthen each time it is named; its competitors are not named within a block, so there is no strengthening of their connections and therefore there is no slowing down when naming *dog* a second time within an experiment or block). In related blocks, the connections between the lexical and semantic networks are often being weakened (e.g., naming *cat* weaken's *dog's* connections to the semantic network). Repetition priming often has very large effect sizes (~100ms; see Navarrete et al., 2012). When averaging across blocks, related blocks may be slower because of weaker repetition priming effects and not due to competition arising from spreading activation. Recall that repetition priming is theorized to be an incremental learning effect and not a spreading activation effect. One way around this conofound is to average naming latencies by trial within a block instead of averaging across blocks.

In fact, a few blocked naming paradigm monolingual studies have shown faciliation in semantically related blocks when analzying naming latencies on a trial by trial basis, but not in semantically unrelated blocks (e.g., Navarrete, Mahon, & Caramazza, 2010; Navarrete, Prato, Peressotti, & Mahon, 2014)[4]. This is difficult for competition-based models to explain. It may indicate that monolingual lexical selection is not competitive in nature. These results do indicate that it is preferable to examine results on a trial by trail basis rather than averaging across blocks.

However, assuming a non-competitive process in the monolingual domain does not resolve how bilinguals control their languages. Even if words do not compete within a language, bilinguals still need a control mechanism to constrain output to only one language. If activation flows to both lexicons, and the semantic to lexical connections are stronger for L1 words than they are for L2 words, this control mechanism would ensure that the most active L1 word is not selected when speaking in L2 (i.e., L1 translation activation > L2 target word activation, resulting in an intrusion error). That control mechanism might be inhibition or it might be some sort of lexical selection mechanism.

Most research on bilingual langauge control uses the language switching paradigm to determine whether inhibition is used, which helps determine whether a bilingual's languages compete. The language switching paradigm has shown inconsistent results (e.g., compare the results of Meuter & Allport, 1999, to Verhoef, Roelofs, & Chwilla, 2009, or to Costa, Santesteban, & Ivanova, 2006; this will be discussed more in chapter two). Very few studies have examined how spreading activation affects naming latency. Those that have tried to do so have used the cyclical paradigm (e.g., Runnqvist et al., 2012). This is problematic. As mentioned

[4] Incremental learning may still have a slowing effect from one trial to the next. However, spreading activation may overpower those effects. Regardless, the fact that facilitation is found when there are no filler trials in the blocked naming paradigm, but interference is found when there are fillers in the cyclical paradigm, suggests two mechanisms are at work.

previously, there is a good chance that the cyclical paradigm creates incremental learning effects, not spreading activation. Thus, the data may have been misinterpreted. In order to study how spreading activation affects bilingual language control, the blocked paradigm must be used, and results analyzed trial by trial.

To conclude this section, this dissertation addresses two related questions regarding bilingual language control. First, *is inhibition used to control language output?* Results from Experiment One suggest that this is the case because spreading activation effects (as manifested by facilitation trial by trial) were abolished after participants switched languages. Second, *has previous research misinterpreted incremental learning effects as spreading activation effects?* Results from Experiment Two indicate that this has happened. When filler trials were presented between semantic neighbors, naming latencies of those semantic neighbors increased. This increase was independent of language switching and number of filler trials. The increase is more easily explained by incremental learning effects than it is by spreading activation. Additionally, results from this dissertation also provide evidence, that within a language, words do not compete with each other for selection.

CHAPTER TWO:

COMPUTATIONAL INSTANTIATION OF THE ICM AND LSM

There has been considerable debate in the bilingual literature regarding the specific mechanism that bilinguals use to control language output. In this chapter, I first explain what the inhibitory control model (ICM) and lexical selection mechanism model (LSM) assume. I then evaluate evidence that supports each. Finally, I present predictions based on computational modeling that examines the effect of language switching on putative spreading activation effects. As detailed below, the LSM and ICM computational models predict that spreading activation will create interference within a language. However, only the ICM computational model predicts that those effects will vanish after a language switch.

The ICM (Green, 1998a) assumes that both lexicons are active initially, and that the lexicons compete. In order to help resolve competition, it proposes that a domain general inhibitory mechanism is involved in controlling language output. Each word in both lexicons is tagged based on which language it belongs to. Words with language tags that do not correspond to the goal of the speaker are inhibited through language task schemas that are controlled by the supervisory attentional system (SAS). The theory behind task schemas and SAS comes from work done by Shallice and Burgess (1996) and Norman and Shallice (1986). A task schema is "a mental device or network that individuals construct or adapt on the spot in order to achieve a specific task" (i.e., speak in L2; Green, 1998a, p. 69), whereas SAS is what directs attention and controls the schemas. One of SAS's jobs in the ICM model is to relay information about a speaker's goal (i.e., speak in L1 when speaking to people who do not know L2) to the language schemas. In essence, SAS activates the correct language schema. Then, the language schema inhibits the non-target language and/or activates the target language. It should be noted that how language tagging occurs or what mechanism is responsible for language tags is not specified in the model. However, Green (1998b) has stated that the function of tags is to ensure that the utterance is compatible with the language goal, and a tag could be a specific marker of langauge for each word (i.e., a language node connected to a lexical node; e.g., the node for *cat* in a computational model is linked with an English node, whereas *gato* is linked to a Spanish node) or an executive process that checks whether the word has come from the correct lexicon. In the latter case, the lexicons may come from separate networks, and the executive process makes sure the output matches the intended goal of the speaker.

Since the ICM assumes L1 words have stronger connections to the semantic network than L2 words do, it applies inhibition to non-target language tags reactively based on the activation level of the non-target words themselves. The more active a non-target word is, the more it is inhibited. Because of this, after a language switch, spreading activation among semantic neighbors will be reduced or eliminated in the language that gets switched out of.

Evidence supporting the ICM predictions comes from two sources in language switching studies: switch costs in naming latencies and differences in the N2 (taken as a measure of inhibition) when measuring ERPs. Under the language switching paradigm, participants are given a language cue and asked to name a picture. The order of language can either be pseudorandom (e.g., a rule that states there should be no more than 3 stimuli from the same language in a row) or predictable (e.g., L1, L1, L2, L2 etc.). According to the ICM, switching into L1 from L2 (i.e., an L1 switch) for an unbalanced bilingual is more costly than switching into the L2 from the L1 ([$RT_{L1Switch} - RT_{L1Stay}$] > [$RT_{L2Switch} - RT_{L2Stay}$]). The logic behind it is that the L1 is stronger than the L2, and therefore a non-target L1 requires more inhibition than a non-target L2. Once a speaker wants to start speaking in L1 again, the strong inhibition of L1 must be overcome, which increases naming latencies relative to L1 stay trials. In other words, the cost of switching into L1 (or L2) is proportional to how much L1 (or L2) was inhibited on previous trials.

As the ICM predicts, several studies have found asymmetric costs in language switching tasks with unbalanced bilinguals, regardless of whether language order is pseudorandomized or predictable (e.g., Costa & Santesteban, 2004; Gollan & Ferreira, 2009; Jackson, Swainson, Cunnington, & Jackson, 2001; Linck, Schwieter, & Sunderman, 2012; Meuter & Allport, 1999; Verhoef, Roelofs, & Chwilla, 2009). Additionally, the more balanced a bilingual is (i.e., the more fluent she is in her L2), the more symmetric the costs should be, since inhibition is applied more equally to both languages. This prediction regarding effects of balance has some empirical support in the literature (e.g., Costa & Santesteban, 2004; Costa, Santesteban, & Ivanova 2006; Meuter & Allport, 1999).

ICM predictions can also be tested with electrophysiology. Consider, for instance, the N2 wave, which is often characterized as a measure of inhibition. It is assumed that a large N2 amplitude indicates greater inhibition (see Folstein & Van Petten, 2008, for a review). Because of this, researchers have measured the N2 response under the language switching paradigm. The ICM predicts the greatest inhibitory response to occur during L2 switch trials because it is at this point that the L1 (i.e., the dominant language) needs to be inhibited. Indeed, some studies have found greater N2 negativity during L2 switches (indicating a stronger inhibitory ERP response) than during L1 switches (e.g., Jackson, Swainson, Cunnington, & Jackson, 2001; Verhoef, Roelofs, & Chwilla, 2009). The foregoing discussion is summarized in Table 1, which shows predictions of the ICM for naming latencies and N2 amplitude

Table 1. *Predictions of the ICM for Naming Latencies and N200 Response*

	Switching into L1 (L1 Switch)	Switching into L2 (L2 Switch)	Staying in L1 (L1 Stay)	Staying in L2 (L2 Stay)
Naming Latency	Greatly increased compared to L1 Stay	Increased compared to L2 Stay	Theoretically the fastest response	Slower than L1 stay, faster than L2 switch
Effect on N2 Response	Weak increase in N2 Response	Strong increase in N2 Response	Little Effect on N2	Little Effect on N2
What is happening to L1?	L1 reactivated after being strongly inhibited	L1 strongly inhibited	L1 remains active	L1 remains strongly inhibited
What is happening to L2?	L2 weakly inhibited	L2 reactivated after weak inhibition	L2 remains weakly inhibited	L2 remains active

In contrast to the ICM, Costa and Caramazza (1999) argue that there is a domain-general lexical selection mechanism (LSM) that chooses from only the intended language's words. Both the L1 and L2 words may be active at the same time through input from the semantic network, but the mechanism only considers words from one language. One might propose that, under such a model, costs occur during language switching because it takes time for the selection mechanism to stop considering one language and start considering the other. Because of the language selection mechanism, it does not matter how active the unintended language word is, and inhibition is not necessary. The activation of a word in one language should not affect the time (and/or difficulty) of choosing a word in the other language. In effect, it allows the bilingual to ignore one language altogether without inhibition. Because the LSM does not rely on inhibition (or overcoming it), it predicts that participants will take the same amount of time switching into L1 as they will when switching into L2 (i.e., symmetrical switching).

Table 2. *Predictions of the LSM for Naming Latencies*

	Switching into L1 (L1 Switch)	Switching into L2 (L2 Switch)	Staying in L1 (L1 Stay)	Staying in L2 (L2 Stay)
Naming Latency	Increased compared to L1 Stay	Increased compared to L2 Stay	Theoretically the fastest response	Slower than L1 stay, faster than L2 switch
What is selection mechanism doing?	Stops considering L2 activation, starts considering L1	Stops considering L1 activation, starts considering L2	Keeps considering L1 activation, ignoring L2	Keeps considering L2 activation, ignoring L1
What is happening to L1?	L1 receives activation from semantic network	L1 receives activation from semantic network	L1 receives activation from semantic network	L1 receives activation from semantic network
What is happening to L2?	L2 receives activation from semantic network	L2 receives activation from semantic network	L2 receives activation from semantic network	L2 receives activation from semantic network

The LSM does lack specificity compared to the ICM. First the model does not specify exactly how and when the lexical selection mechanism works. Because of this, the lexical selection mechanism, if it exists, might reflect another executive function similar to what has been referred to as *shifting* and *updating* (see Lehto, 1996; Miyake, et al., 2000; Monsell, 1996;

Morris & Jones, 1990; Posner & Petersen, 1990). The LSM does not make any predictions regarding the N2. See Table 2 for predictions of the LSM regarding naming latencies.

Comparing Tables 1 and 2, it is clear that the models differ primarily in what happens to the non-target language during switch trials. For example, according to the ICM during L2 switch trials, L1 becomes inhibited. It must then be reactivated on L1 switch trials. On the other hand, the LSM assumes that during L2 switch trials, L1 continues to receive activation from the semantic network. Thus, there is no need to reactivate it on L1 switch trials.

The LSM has been promoted by Costa and colleagues. They have conducted a few experiments that provide some support for their view. Costa and Santesteban (2004) conducted a language switching experiment with both balanced and unbalanced bilinguals as well as trilinguals who were balanced in L1 and L2 but unbalanced in L3. As predicted by the ICM, they found asymmetrical switching costs for unbalanced bilinguals, and symmetrical switching costs for balanced bilinguals. However, contrary to what the ICM predicts, they also found symmetrical switching costs when trilinguals switched between their L1 and L3. It should be noted that the trilinguals were fluent in their L1 and L2, but not fluent in their L3. Costa and Santesteban argued that symmetrical switch costs for L1 and L3 indicate that balanced fluency in two languages leads to the development of a lexical selection mechanism that can then be applied to other languages that are learned later. It should be noted that this explanation has been criticized because it lacks parsimony (Verhoef, Roelofs, & Chwilla, 2009), especially since it does not answer why bilinguals need to change the mechanism they use for language control as they become more proficient. However, Costa, Santesteban, and Ivanova (2006) replicated the results for proficient bilinguals who learned their second language late in life and when controlling for language similarity (by comparing switch costs for *Spanish-Catalan* bilinguals to

Spanish-Basque bilinguals). They argue that proficiency is the main factor in determining whether a bilingual uses an inhibitory mechanism or lexical selection mechanism to control language output. Less proficient bilinguals rely on it, whereas proficient bilinguals employ a lexical selection mechanism that considers only one language at a time.

The ICM and LSM are attractive theories. However, the evidence is mixed regarding which best describes how bilinguals control their languages. For example, Verhoef, Roelofs, & Chwilla (2009) argue that asymmetric switch costs are found simply because L1 stay trials are so much faster than other trials. Some studies have found a *reverse dominance effect* in language switching paradigms that neither theory can account for easily (e.g., Christoffels, Firk, & Schiller, 2007; Costa & Santesteban, 2004; Costa, Santesteban, & Ivanova, 2006; Gollan & Ferreira, 2009; Verhoef, Roelofs, & Chwilla, 2009). The reverse dominance effect is when participants take longer to name pictures in their dominant language than their non-dominant language, regardless of whether the trial is a switch or stay. It is usually found with symmetrical switching costs. Some studies have demonstrated asymmetrical switching costs when unbalanced bilinguals/trilinguals switch languages (e.g., Linck, Schwieter, & Sunderman, 2012; Meuter & Allport, 1999) while others have not (e.g., Costa & Santesteban, 2004). Some have found increased N2 amplitudes during L2 switch trials indicating an inhibitory process (e.g., Jackson, Swainson, Cunnington, & Jackson, 2001), while others have not (e.g., Christoffels, Firk, & Schiller, 2007).

These discrepancies suggest the language switching paradigm may not be adequate in determining which of the two models is most accurate. Additionally, both the ICM and LSM predict symmetric switch costs for balanced bilinguals. Thus, for balanced bilinguals it is impossible to determine what mechanism they use (i.e., inhibition or lexical switch) based on switch costs alone. I propose that a clearer test of the models' predictions can be obtained by examining the effects of category membership across languages. Consider, for example, a blocked naming task in which items vary as to whether they share a category or not, both within and across languages. If a word that is categorically related to its previous trial has to be named within a language, one would expect spreading activation from the previous trial to affect it (e.g., increasing the overall local activation which creates competition; increasing naming latencies). Before a language switch (i.e., when bilinguals are speaking in their L1 only), the LSM and ICM predict similar reaction times for categorically related stimuli: naming latencies should keep increasing trial by trial as competition builds up in one of the lexicons. Thus, blocks of related stimuli should have longer naming latencies than blocks of unrelated stimuli as long as a participant does not switch languages.

The difference between the models happens after switching languages. The ICM predicts naming latencies to be the same on trials after a language switch, regardless of whether it was categorically related or unrelated to a block's previous trials. The underlying mechanism is explained by Green (1998a):

> The controlling schema [can]... reactively inhibit competitors in the non-target language. However, if there is a change of language then any lemmas in the previously active language will become inhibited… *This should lead to the abolition of both cross-language and within-language competitor priming* [emphasis added]. (p.75)

In other words, the ICM assumes that any activation that builds up during the stay trials is counteracted by inhibition on the switch trials. For this reason, it would not matter if a stimulus right after a switch was categorically related to the previous trials or not; its naming latency would be the same since priming effects were eliminated during the switch.

In contrast, the LSM predicts that the naming latency of a trial after a switch depends on whether it is semantically related to previous trials: If the trial is semantically related, its latency will be greater than that of a trial that is not semantically related. This is due to the absence of inhibition in their theory. Costa and Caramazza (1999) explain that the "selection mechanism… picks out the most highly activated lexical node at a given moment" from only the intended language and "lexical selection is achieved by a system that does not require the active inhibition of the lexicon-not-in-use" (p. 232).

In summary, the traditional way to test the ICM and LSM has been to use the language switching paradigm. However, that paradigm has produced inconsistent results. Another way to examine which theory better approximates reality is to test whether spreading activation effects are abolished after a language switch. To test the two theories, I instantiated the ICM and LSM in computational models to closely examine their predictions and to verify the internal consistency of those predictions with the prior verbal descriptions of the models. The models have been implemented in R to predict naming latencies from one trial to the next based on a trial's language, trial type (switch, stay) and semantic-relatedness to the previous trial. Simulations show that the ICM predicts that naming latency will be the same after a language switch, regardless of whether the previous trial is from the same semantic category as the current one. Simulations of the LSM show that it predicts naming latencies will be greater on trials that are semantically related to previous trials compared to trials that are not, even if there was a language switch on the previous trial. The code for the ICM and LSM models can be found in an R-package called "ICMLSM" on Github (Lowry, 2018). Detailed information about both models can be found in Appendix A.

Brief Architecture for the Two Models

Overview

Since the ICM and LSM predict different outcomes depending on whether semantic categories change from one trial to the next, I created two computational models (one for the LSM, one for the ICM) that predict naming latencies on a trial by trial basis. The models use 3 inputs to estimate naming latencies: language (L1 or L2), type of trial (SWITCH or STAY) and semantic-relatedness of trial n to trial n-1 (TRUE or FALSE). The models increase and decrease the values of three main parameters for each language to determine naming latencies: target word activation levels, last target activation level, and other distractors activation level. There are also noise parameters that change trial by trial. Each noise parameter is a randomly selected value based on an ex-Gaussian distribution to add variability into the model. On each trial, initial activation levels and maximum activation levels are also recorded for target and distractor words. At the end of each trial, activation decays. More explanation of the models can be found in Appendix A.

On trials where participants stay in a language, activation either builds up or resets depending on whether the previous trial was semantically related. The two models differ in how they treat switch trials. The ICM computational model estimates switch costs by considering how long it takes to inhibit the unintended language and activate the target language. The LSM assumes that switching languages does not need inhibition. In sum, for the ICM, activation resets on trials that are semantically different from the previous trial and after switch trials. For the LSM, activation only resets when the current trial is semantically different from the previous trial. See Figures 2 and 3 for a diagram of the ICM and LSM respectively.

Figure 2. A

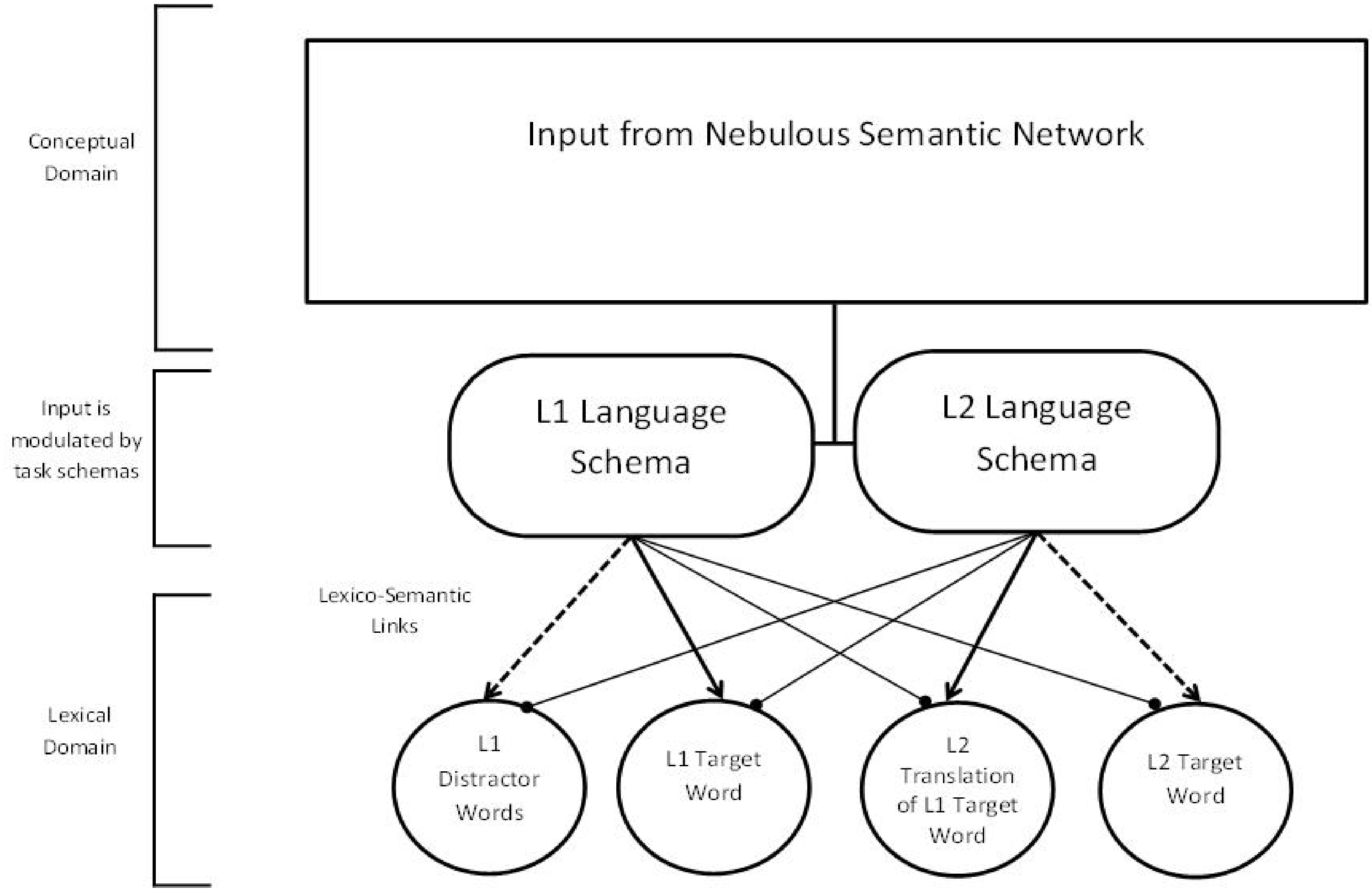


Diagram of the ICM Computational Model. Dashed lines indicate that distractor words (i.e., semantically similar words) receive activation through spreading activation)

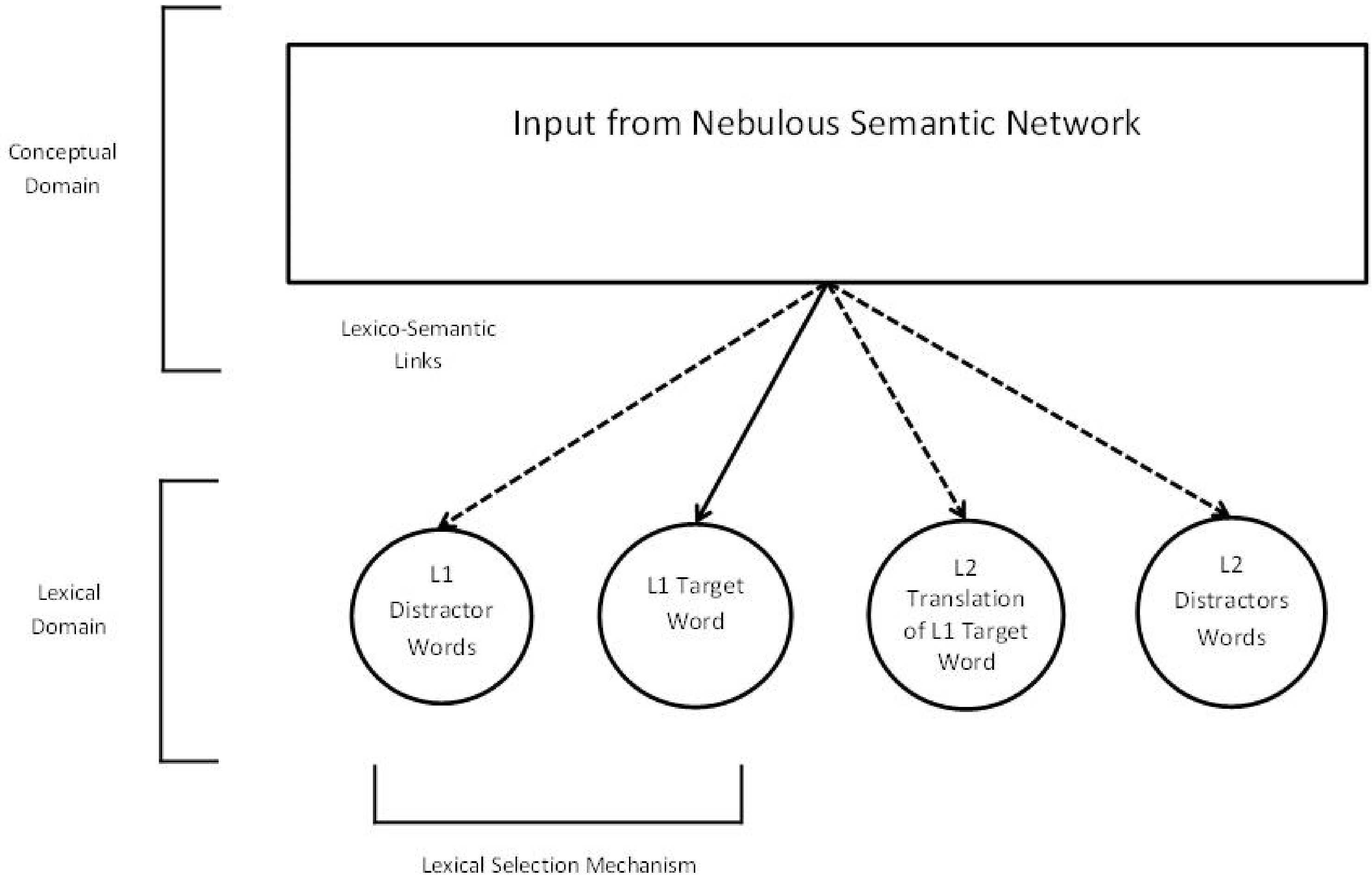


Figure 3. A Diagram of the LSM Computational Model. Dashed lines indicate that distractor words (i.e., semantically similar words) receive activation through spreading activation)

The ICM Computational Model

The ICM computational model tries to represent activations of a target word, its semantic neighbors, and unrelated words on both stay and switch trials. The total activation of a word ($T_{j,k,l,m}$) is calculated by adding activation from the semantic network, or removing activation through decay or inhibition. The subscripts *j, k, l* and *m* stand for *type of trial* (j; stay [*j*=1], switch [*j*=2]), *type of word* (*k*; target [k=1], previous target [*k*=2], and other distractors [*k*=3]), *language* (l; dominant language [*l*=1], non-dominant language [*l*=2]), and *m* refers to *whether the word is in the intended language or unintended language* (intended [*m*=1], unintended [*m*=0]). The following equations are used to calculate a word's activation level on stay trials at any given point in time:

$$(1)\ T_{1,k,l,m} = Inihibition\ from\ Schema + Activation\ from\ Semantic\ Network$$

$$(2)\ T_{1,k,l,m} = (A_{0j,k,l,m})e^{-(\varepsilon_m h_l t)} + p_{k,m}\left(\frac{1}{(1 + L_{j,l}e^{-t})}\right)$$

where A_0 represents a word's initial activation at the beginning of a trial. t represents the total time activation is applied to a word (*note:* one unit of t is equal to 20ms). h_l is the inhibition parameter, and its value depends on the relative strength of a bilingual's language. p represents the proportion of activation a word receives from the semantic network based on whether it is the target word and in the intended language. Target words in the intended language receive most of the activation (i.e., $p_{1,1}$=0.75 or 75%). Distractors in the intended language split the remaining activation. Distractors in the unintended language receive no activation (e.g., $p_{1,2}$=0). ε determines whether the word is inhibited on a given trial (ε is equal to 0 if the word is in the intended language [*m*=1], and 1 if it is the unintended language [*m*=0]). L determines how fast a word receives activation from the semantic network

Note that for words in the intended language (i.e., when $\varepsilon = 0$), there is no inhibition (i.e., $e^0 = 1$ in the first part of Equation Two), and activation from the semantic network is added to the initial activation at the beginning of the trial. Conversely, words in the unintended language receive no activation (i.e., $p_{k,1}$=0) from the nebulous semantic network, but they are inhibited based on their initial activation levels.

The ICM assumes a fully competitive system. In order for the target word to be chosen on a stay trial, its activation level must be some ratio (*V;* the competition parameter) of the sum of all other distractor activations in both languages. In other words, for a target to "win" its activation must be some ratio greater than or equal to the sum of all the activations for the distractors in the target language plus the sum of the activations for all the translated words in the non-target language. If the target is in the dominant language, it would be represented by the following equations:

$$(3)\ \ Target\ Activation \geq V(Sum\ of\ All\ Other\ Word\ Activations)$$

$$(4)\ \ T_{1,1,1,1} \geq V(T_{1,2,1,1} + T_{1,3,1,1} + T_{1,1,2,2} + T_{1,2,2,2} + T_{1,3,2,2})$$

If the target is in the non-dominant language, the equation is similar, except the *l* subscript changes:

$$(5)\ \ T_{1,1,2,1} \geq V(T_{1,2,2,1} + T_{1,3,2,1} + T_{1,1,1,2} + T_{1,2,1,2} + T_{1,3,1,2})$$

By replacing the target activation (e.g., $T_{1,1,1,1}$) with T_x and all other non-target words (distractors and translations) with T_d, then V can be represented by the following equation:

$$(6)\ \ \mathrm{V} \leq \left(\frac{T_x}{\sum T_d}\right)$$

Once V is less than or equal to the ratio of the target word and the sum of the distractors, then the target is selected. Until this happens, activation or inhibition is applied to each word. If V=0.55, then one can calculate the time needed by replacing T_x and $\sum T_d$ with their respective equations, and solve for t. t is then converted to milliseconds and is added to a noise parameter. The noise parameter changes with each trial and is randomly selected from an ex-Gaussian distribution, which has three parameters: mu (μ), sigma (σ) and tau (τ) (see Luce, 1986).

Because the distractor/translation and target activations are all functions of t, one could also plug in the equations for them into equation six and calculate its inverse to figure out how much time it would take to choose a target word based on a given value of the Competition Parameter (V). The result is plotted in Figure 4. It should be noted that the shape of the curve depends on the initial starting activation levels of all the words, and the curve may be different trial by trial. t can then be added to the noise parameter to find the total time for the trial.

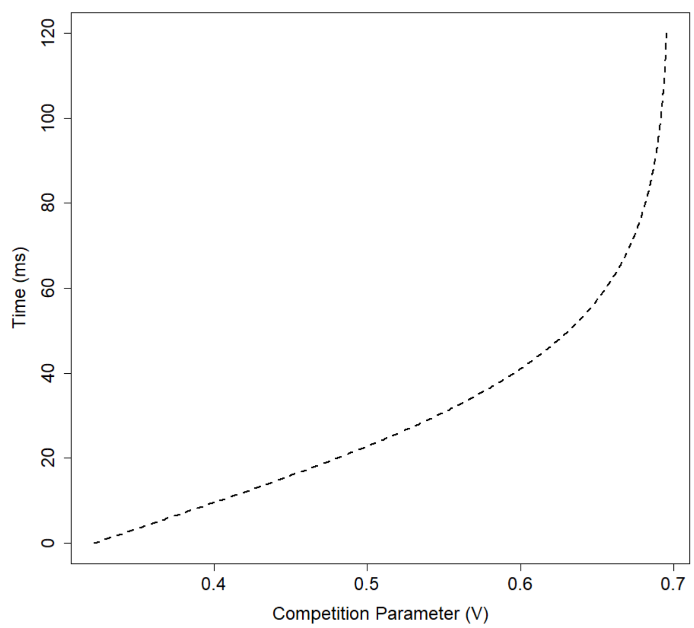


Figure 4. The time it takes to choose a target word in the lexicon as a function of the Competition Parameter (V). The language strength parameters (L) were set to 1.5, the inhibition parameters (h) were set to 1.0, initial activations were set to 3.0 and 1.5 for L1 words and L2 words respectively, and c was set to 0.01. The Noise Parameter has not been added to the time.

The model behaves similarly on switch trials. Note that words in the unintended language on trial n-1 are now in the intended language on trial n. This means that the subscript m switches between the two languages. The ICM assumes that these previously inhibited words in the intended language must be reactivated on switch trials. This takes time, and it is assumed this is a separate process that happens before semantic activation spreads to the intended language's words. I will call this the reactivation stage. The amount of reactivation at any given point in time is represented in the following equation by $T_{\{0\}_{j,k,l,m}}$:

$$(7)\ \ T_{\{0\}j,k,l,m} = \left(A_{\{0\}j,k,l,m}\right)e^{-(\varepsilon_m h_l t_s)} + \varepsilon_m\left(-\frac{R_l Y_l}{e^t+1}\bigg|_0^{t_s}\right)$$

where the rate of reactivation (Y) depends on how strongly the intended language's words were inhibited (h) and the overall strength of the language (L) on the previous trial. Thus, Y is proportional to the sum of the language strength parameter on stay trials plus the inhibition parameter (i.e., $Y \propto L + h$). R is the normal resting activation of a language. It is equal to the initial activation of words on trial one of a simulation. t_s is the switch cost, and represents how much time has passed in this reactivation stage. Once $T_{\{0\}}$ is greater than or equal to R, then the lexical selection stage begins and T_0 acts like the initial activation in Equation Two. The equation then becomes

$$(8)\ \ T_{2,k,l,m} = \left(T_{\{0\}j,k,l,m}\right)e^{-(\varepsilon_m h_l t)} + p_{k,m}\left(\frac{1}{(1+Y_l e^{-t})}\right)$$

t can then be calculated in a similar manner to how it is found in stay trials. However, in order to find the total time it takes to select a word on a switch trial, t_s must be added to t. Then, it is added to the noise parameter. Note also, that the language strength parameter (L) has been replaced with the rate of reactivation parameter (Y). It is assumed that the rate of activation from the semantic network is affected by inhibition, which is why Y is used instead of L.

After the target is chosen on stay and switch trials, activation for all words decay based on the decay function and inter-stimulus interval (ISI) found in Appendix A. After a trial is finished, and before a semantically related trial, the target word's activation becomes the *previous distractor's* activation, and the new target's activation is calculated based on the *other distractor's* activation. This allows spreading activation to occur and increases competition on semantically related trials. At the beginning of non-semantically related trials, the target and distractor activations are reset to the resting activation level (*R*).

The LSM Computational Model

In many respects, the LSM computational model is very similar to the ICM computational model. There are two exceptions. The first is that there is no inhibition in the model. Because of this, spreading activation affects both the target language and non-target language. Additionally, the equations for both stay and switch trials are the same:

$$(9)\ T_{1,k,l,m} = \ Activation\ from\ Semantic\ Network$$

$$(10)\ T_{1,k,l,m} = A_{0j,k,l,m} + \ p_{k,m}\left(\frac{1}{(1 + L_{j,l}e^{-t})}\right)$$

Note that there is no inhibition applied to any of the words. Additionally, the LSM assumes that only words within a language compete. Instead of the target activation needing to be some ratio larger than all the distractors (i.e., within and between language), it only needs to be some ration larger than the distractors in its language (i.e., the intended language). For a stay trial in L1, this would be represented by the following equations:

$$(11)\ Target\ Activation \geq \ V(Sum\ of\ Distractor\ Activations)$$

$$(12)\ T_{1,1,1,1} \geq \ V(T_{1,2,1,1} + \ T_{1,3,1,1})$$

t can be found using similar calculations in the ICM computational model (see Equation 6).

If there is no inhibition to be overcome, how does one go about determining switch costs? This is somewhat problematic because the lexical selection mechanism is poorly defined in the literature. One way to model switch costs is by changing the language strength parameter on switch trials. By making it larger on switch trials, the curve of the logistic function is less steep, and it takes longer for the target to be selected. This is how switch costs are manipulated in the LSM computational model.

Activation decays during the inter-stimulus interval similarly to the ICM computational model. More detail can be found in Appendix A. During the inter-stimulus interval on semantically related trials, the target word's activation becomes the *previous distractor* word's activation, and the new target activation is calculated based on the *other distractors* activation level. At the beginning of non-semantically related trials, the target and distractor activations are reset to the resting activation level (*R*).

Simulations

Two-hundred "experiments" were simulated for each model. Each simulated experimented consisted of 40 "participants" naming 768 trials. Trials were grouped into two types of sub-blocks: mixed and uniform. Each sub-block type consisted of 6 trials. In uniform sub-blocks, all stimuli came from the same semantic category. In mixed sub-blocks, semantic category changed on trial 5. All sub-blocks had the same trial type order: *stay, stay, stay, switch, switch, stay.* Because uniform sub-blocks are all semantically related, the LSM predicts that there will be semantic interference on trials five and six, even after the language switches on trial four. However in mixed sub-blocks, changing semantic categories on trial five will abolish these effects. Thus, the LSM predicts greater naming latencies for uniform sub-blocks on trials five and six than for mixed sub-blocks. On the other hand, the ICM predicts that inhibition applied to the non-target language on trial four will abolish interference effects on trials five and six during uniform sub-blocks. In other words, the ICM predicts similar reaction times on trials five and six for both mixed and uniform sub-blocks.

Parameter values for each model were chosen by hand and were similar to those chosen in Appendix A with one exception. Noise was introduced into the simulations through the noise parameters, mu (μ), sigma (σ) and tau (τ), which varied for each participant. They were based on an ex-Gaussian distribution. Thus, each participant was assigned a unique ex-Gaussian distribution that helped determine a participant's reaction times on each trial. The mean and standard deviation of the distribution from which each μ was taken was 520ms and 20ms respectively. The mean and standard deviation for each τ was 400 and 10, and the mean and standard deviation for σ was 100 and 10. These values were based on pilot work and previous studies that I have run in the lab. Simulations for each model can be run in R in the ICMLSM package.

ICM Computational Model Results

Naming latencies were averaged across simulations for each trial and sub-block type. For a summary of the results, see Figure 5 . Trials one through three were also analyzed to examine how the ICM computational model predicts within-language competition due to semantic relatedness. A regression analysis with trial number (one through three) as the predictor variable was used to predict mean reaction times. It was found that each subsequent trial significantly increased reaction times ($\beta = 24.95$, $p<.01$), indicating that semantic relatedness on the previous trial interfered with naming on the current trial.

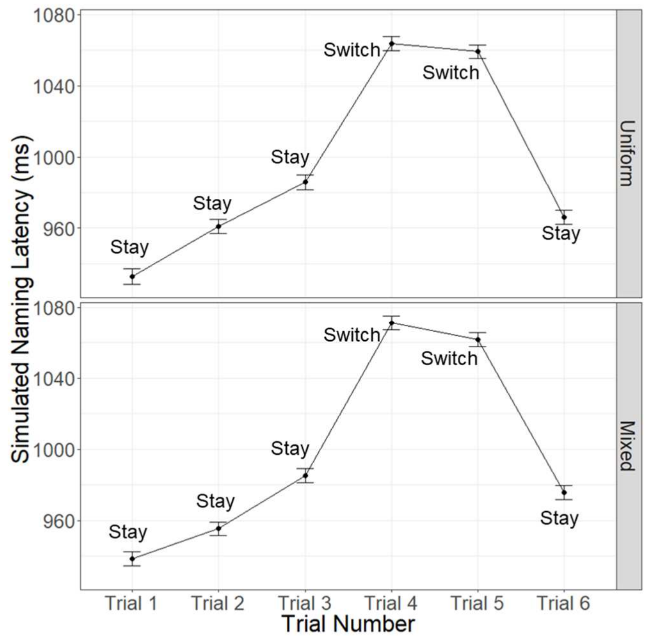


Figure 5. ICM Results of 200 Simulations for both Uniform and Mixed Sub-Blocks. Trials one through three and trial six are stay trials. Trials four and five are switch trials. Error bars represent standard errors.

In order to determine if spreading activation effects were abolished after a language switch, naming latencies of mixed and uniform sub-blocks were compared on trials five and six. On the fifth trials (i.e., second switch trial), naming latencies in uniform sub-blocks (*M*= 1059, *SD* = 53.20) were 2ms faster than naming latencies in mixed sub-blocks (*M*= 1061, *SD* = 54.31). In roughly 52% of the simulations on trial five, uniform sub-blocks were faster than mixed sub-blocks, $\chi^2(1, N=200) = 0.16$, p=0.69. On the sixth trials (i.e. a stay following a switch), naming latencies in uniform sub-blocks (*M*= 966, *SD* = 56.85) were 9.51ms faster than naming latencies in mixed sub-blocks (*M*= 975, *SD* = 58.02). In 52% of the simulations or trial six, uniform sub-blocks were slower than mixed sub-blocks, $\chi^2(1, N=200) = 0.16$, p=0.69. The results indicate that the ICM predicts very little, if any, difference between uniform or mixed sub-blocks for trials five and six.

LSM Computational Model Results

Naming latencies were analyzed similarly for the LSM computational model. For a summary of the results, see Figure 6. Trials one through three were also analyzed to examine how the LSM computational model predicts within-language competition due to semantic relatedness. A regression analysis with trial number (one through three) as the predictor variable was used to predict mean reaction times. It was found that each subsequent trial significantly increased reaction times by roughly 22 milliseconds ($\beta = 21.68$, $p<.01$), indicating that semantic relatedness on the previous trial interfered with naming on the current trial.

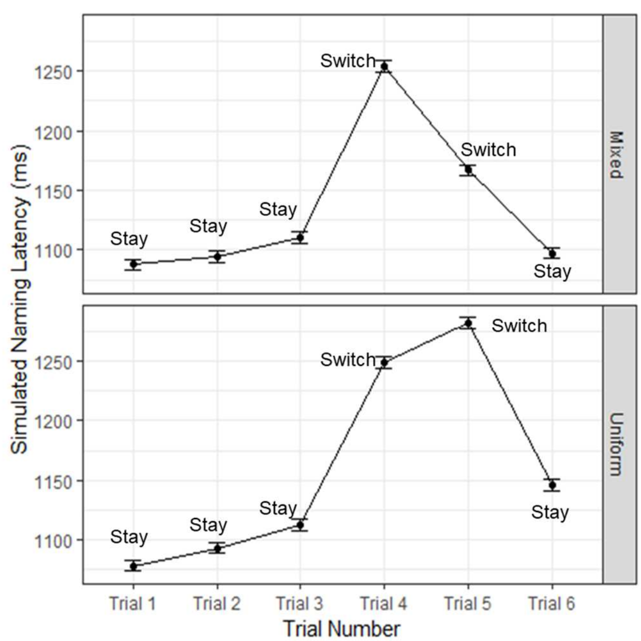


Figure 6. LSM Results of 200 Simulations for both Uniform and Mixed Sub-Blocks. Error bars represent standard errors.

On trial five, naming latencies in uniform blocks (*M* = 1358, *SD* = 63.74) were 134ms slower than in mixed sub-blocks (*M* = 1223, *SD* = 66.12). In 92.5% of the simulations on trial five, uniform sub-blocks were slower than mixed sub-blocks, $\chi^2(1, N=200) = 88.17$, $p<0.001$. On trial six, naming latencies in uniform blocks (*M* = 1220, *SD* = 62.42) were 68ms slower than in mixed sub-blocks (*M* = 1152 *SD* = 62.42). In roughly 93% of the simulations on trial six, uniform sub-blocks were slower than mixed sub-blocks, $\chi^2(1, N=200) = 36.73$, $p<.001$. The results indicate that the LSM computational model predicts naming latencies to be longer on trials five and six for uniform sub-blocks than for mixed sub-blocks, and that there is a large effect size. In other words, spreading activation effects were not abolished after a language switch.

Discussion

In this chapter, I reviewed the inhibitory control model (ICM) and lexical selection mechanism model (LSM). According to the verbal theories, the ICM predicts that semantic interference effects are abolished after a language switch; the LSM predicts that semantic interference effects are not abolished after a language switch. In order to test these ideas, I created two computationally similar models instantiating each verbal theory. Results of simulations showed that, as expected, semantic interference effects disappeared after a language switch for the ICM (see Figure 5), but not for the LSM (see Figure 6).

Note that semantic interference was found in the first three trials of a sub-block for both computational models. This reflects the fact that, for both the ICM and LSM, activating semantically-related neighbors of a target word creates competition within a language. It is assumed that spreading activation is the underlying mechanism. However, some theories of monolingual language lexical access argue against within-language competition and have found facilitation from one trial to the next experimentally (e.g., Navarrete, Del Prato, & Mahon, 2012; Navarrete, Mahon, & Caramazza, 2010; Navarrete, Prato, Peressotti, & Mahon, 2014).

The next chapter addresses the predictions made from the simulations in this chapter. Namely, does a language switch diminish the effects of spreading activation? If so, this would indicate that inhibition is used to control activation from a bilingual's two lexicons and would support the ICM. If not, another mechanism would be implicated, supporting the LSM. Additionally, it will examine whether facilitation or interference is found during the first three trials of a sub-block. If interference is found, this would support models that assume competition among words in the lexicon. Conversely, if facilitation is found, this would support a non-competitive model of lexical selection.

CHAPTER THREE:

EXPERIMENT ONE – TESTING WHETHER SWITCHING LANGUAGES AFFECTS SPREADING ACTIVATION

In Chapter Two, simulations of the LSM and ICM computational models tested how switching languages affected interference effects. The ICM computational model predicted no interference effect. The LSM computational model predicted a large one. Both models predicted within language interference from a semantic neighbor named on trial n-1, and both assume that spreading activation from the semantic network is the underlying mechanism that creates competition. The purpose of this chapter is to test those predictions experimentally. If language switching eliminates interference effects, then this would provide evidence for the ICM. If language switching does not eliminate interference effects, this would provide evidence for the LSM. Additionally for the LSM, any spreading activation effects found after a language switch should follow the same pattern that occurred before the language switch. It would be problematic for the LSM if priming were found when naming semantic neighbors within a language, but interference found after a language switch, and would suggest that a mechanism other than spreading activation is responsible for the interference after a language switch.

To date, I know of no studies that have tested how language switching affects spreading activation of semantically-related stimuli from one trial to the next. There have been at least three studies that examined cumulative semantic interference (Hong & MacWhinney, 2011; Lee & Williams, 2001; Runnqvist, Strijkers, Alario, & Costa, 2012). Recall that the cyclical paradigm has participants name semantically related pictures that are separated by filler trials. In Chapter One, I argued that this paradigm may not measure the effects of semantic priming. Rather, it may measure the effects of incremental learning. Evidence supporting this claim comes from studies that show cumulative semantic interference is unaffected by the number of filler trials between semantic neighbors (e.g.,Damian & Als, 2005; Howard, Nickels, Coltheart, & Cole-Virtue, 2006).

What is especially problematic in the bilingual literature is that experimental results from the cyclical paradigm have been used to make conclusions about whether bilinguals use inhibition to counteract spreading activation. For example, Runnqvist et al. (2012) state their interpretation of what the ICM predicts under the cyclical paradigm:

> the ICM predicts that the CSI effects typically observed in a sequence such as '*cat – tree – hand – dog – flower – star – horse'* should be canceled out – both within and between languages – in a language alternating sequence such as '*cat – árbol* [tree] – *mano* [hand] – *perro* [dog] – *flower – star – horse'*. (p. 853)

Runnqvist et al. tested this prediction using the cyclical paradigm, and found that language switching did not cancel out cumulative semantic interference effects. They then argued against theories that posit that there is global inhibition of the non-target language.

However, if cumulative semantic interference under the cyclical paradigm is created by a learning mechanism and not by spreading activation (see Oppenheim, 2010), then one cannot so easily dismiss the ICM. The purpose of inhibition is to control rampant activation in the unintended lexicon. Because naming semantically related stimuli is separated by filler trials under the cyclical paradigm, one might reasonably expect that rampant spreading activation among semantic neighbors naturally decays during those filler trials. In other words, spreading activation from naming a semantically related stimulus on trial *n*-5 should have significantly decayed when naming a stimulus on trial *n.* Theoretically, there is no need to inhibit activation that has already decayed, and subsequently a lack of inhibition would not be what is causing naming latencies on trial *n* to be greater than naming latencies on trial *n*-5.

The experiment in this chapter uses an alternative method to test whether spreading activation effects are eliminated after a language switch: the blocked naming paradigm. Under the blocked naming paradigm, there are no filler trials. Semantically related stimuli are presented one after another. In this way, there is less time for spreading activation to decay. Thus, I can specifically test whether switching languages affects naming latencies, and compare the results to the simulations in Chapter Two. The experiment is similar to the simulations. Participants were asked to name semantically-related stimuli in mixed and uniform sub-blocks. Each sub-block consisted of six stimuli. In mixed sub-blocks, the first four stimuli came from one semantic category, and trials five and six came from another category. In uniform sub-blocks, all six stimuli came from the same semantic category. There are three fundamental questions this experiment can address. **(1) Does a language switch abolish semantic interference?** The ICM predicts that any spreading activation effects should be eliminated after a language switch. Thus, a mixed and uniform sub-block should have similar reaction times on trials five and six. The LSM predicts that spreading activation effects will not be eliminated after a language switch. Thus, uniform sub-blocks should have different naming latencies on trials five and six compared to mixed sub-blocks. **(2) Is there within-language competition among lexical entries?** If there is competition, then reaction times should increase from one trial to the next on stay trials. If there is not, then no interference or facilitation should be observed. **(3) Which model (ICM or LSM) best fits the experimental data?** This can be tested by examining the predictions made in

Chapter Two to the averaged trial x sub block means in the experiment, and by fitting the models to the individual participant data and examining the root mean square (RMSE) of the models.

Method

Participants

45 English-Spanish speaking bilingual participants (71% female; 73% rated English as their L1) were recruited through the USF psychology department participant pool. Two participants were removed due to not meeting the requirements of the study. Additionally, one participant only finished 6 experimental blocks due to computer error. In line with the literature on bilingual language production and comprehension (e.g., Caramazza, 1997; Linck, Schwieter, & Sunderman, 2012; Meuter & Allport, 1999; Moreno, Federmeier, & Kutas, 2002), subjective questionnaires regarding their age of acquisition as well as self-ratings of their reading, writing and speaking ability of their languages were assessed using Likert scales (see Appendix B). In addition, they were given a more objective vocabulary measure, the Multilingual Naming Test (MINT; Gollan, Weissberger, Runnqvist, Montoya, & Cera, 2012). See Table 3 for information on participants' self-ratings of language ability and results of the Multilingual Naming Test.

Stimuli

600 x 600 pixel color photographs from eight semantic categories were used as stimuli (6 pictures per category). The categories were *birds, body parts, clothes, fruits, furniture, music, vehicles* and *weapons.* Each stimulus was associated with a word to be named in the experiment. Between languages, words were controlled for in terms of word frequency, familiarity and prototypicality. Word frequency information for the picture names was taken from the Corpus of Contemporary English (COCA; Davies, 2008-2017) and Corpus del Español (Davies, 2002-

2017). Familiarity and prototypicality ratings were taken from Schwanenflugel & Rey (1986). Stimuli, norming data and relevant properties of the words are presented in Appendix C.

Table 3. *Participants' language proficiency in Experiment One.*

	Language	
Measure	L1	L2
Self-Ratings		
Speaking (out of 7)	6.48 (0.7)	6.02 (0.8)
Reading (out of 7)	6.67 (1.0)	5.5 (0.9)
Writing (out of 7)	6.24 (1.2)	6.14 (1.0)
Age of Acquisition	2.23 (3.3)	4.48 (6.1)
MINT (% correct)	90 (10)	74 (13)

Note: Means of each measure are given with standard deviations in parentheses

Apparatus.

Stimuli were presented using OpenSesame software on lab computers (Dell Optiplex 760). A microphone recorded participants' responses in order to evaluate naming latencies. Naming latencies for each trial were measured by a virtual voice-key, and verified in Praat (Boersma, 2006) and R.

Procedure

Stimuli were presented in the center of a 15 inch 1600 x 900 pixel dell computer screen. Participants were seated roughly 60cm from the screen, with stimuli subtending a visual angle of roughly 10 degrees. After participants were familiarized with the pictures and their corresponding names, they completed a practice session. During the practice session, participants named each of the stimuli twice on the computer screen in their L1 and L2. They then started the experiment. They were asked to name the pictures as quickly and accurately as possible.

Language was cued based on the background color of the picture (*grey* or *light blue*), and background color was counterbalanced across participants. A single trial consisted of a fixation point, presentation of a stimulus and inter-stimulus interval. To make sure participants did not become accustomed to the timing of the pictures, the fixation point's duration varied between 250 and 700ms across trials based on a uniform distribution. The mean of the uniform distribution (500ms) is the same value input for the ISI in the computational models. Stimuli were presented on a screen until a participant responded or until 3000ms passed, whichever was shorter. A recording of the response started at the onset of the stimulus, and naming latencies were measured in milliseconds from the onset of the stimulus until the participant responded. Naming latencies were determined by a virtual voice-key. The inter-stimulus interval lasted 1500ms after the participant responded. If a participant failed to respond within 3000ms (i.e., a timeout), the program proceeded to the next trial. See Figure 7 for a representation of a single trial.

Participants named pictures in eight blocks. Each block contained 96 trials: 48 trials were named in English, and 48 were named in Spanish. Within each block, pictures were grouped into sub-blocks. Each sub-block consisted of 6 trials. Sub-blocks were divided into two types: uniform and mixed. Both types of sub-blocks cued trials according to the same language pattern (i.e., *stay, stay, stay, switch, switch, stay*).

In uniform sub-blocks, all trials came from the same semantic category. In mixed sub-blocks, semantic category changed on trial five. Each sub-block had a major semantic category, from which its words were quasi-randomly ordered. Mixed sub-blocks had a major semantic category (associated with the first 4 trials) and a minor semantic category (associated with the last two trials), with words from each being quasi-randomly selected. Picture stimuli were not repeated within a block until all pictures from that category had been named. Additionally, each trial number across the sub-blocks was controlled for in terms of prototypicality, familiarity and word frequency.

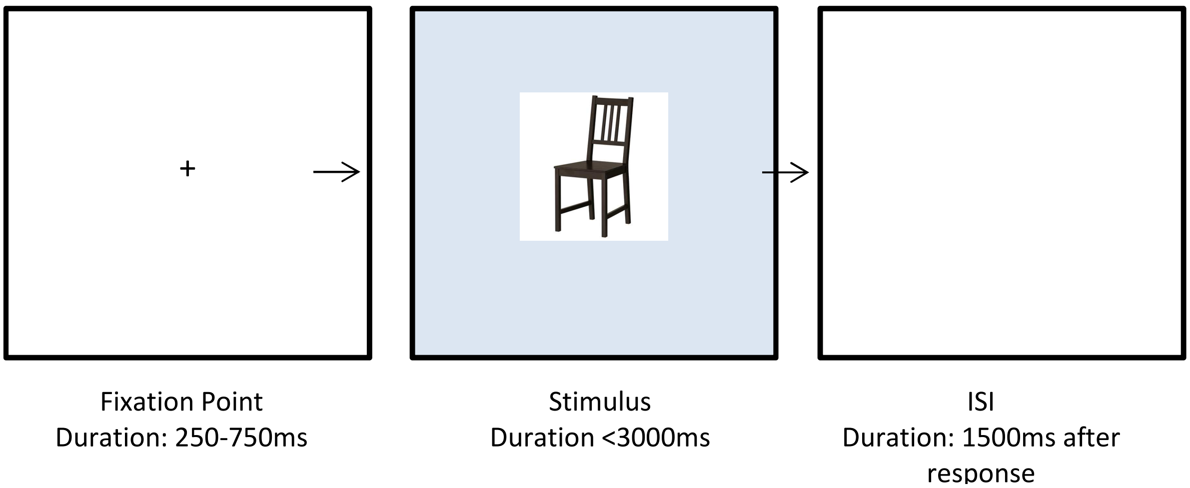


Figure 7. A representation of a single trial. The color of the background cued participants to speak in either L1 or L2

In total, each participant was presented with 8 blocks of trials. Each block consisted of 16 sub-blocks: eight uniform sub-blocks and eight mixed sub-blocks. Within each block, words were presented once in English and once in Spanish, and this was counterbalanced. Type of sub-block alternated. Additionally, type of sub-block presented first within a block alternated. The order of the blocks was presented to participants according to a Balanced Latin Square design. In total, Participants saw 768 trials (8 blocks, each block consisted of 16 sub-blocks consisting of 6 words).

Results

Descriptive Statistics

Descriptive statistics are given in each table for each statistical analysis. However, a summary of the reaction time data as a function of sub-block type and trial within sub-block can be found in Figure 8. Predictions from the computational models have been provided as a reference.

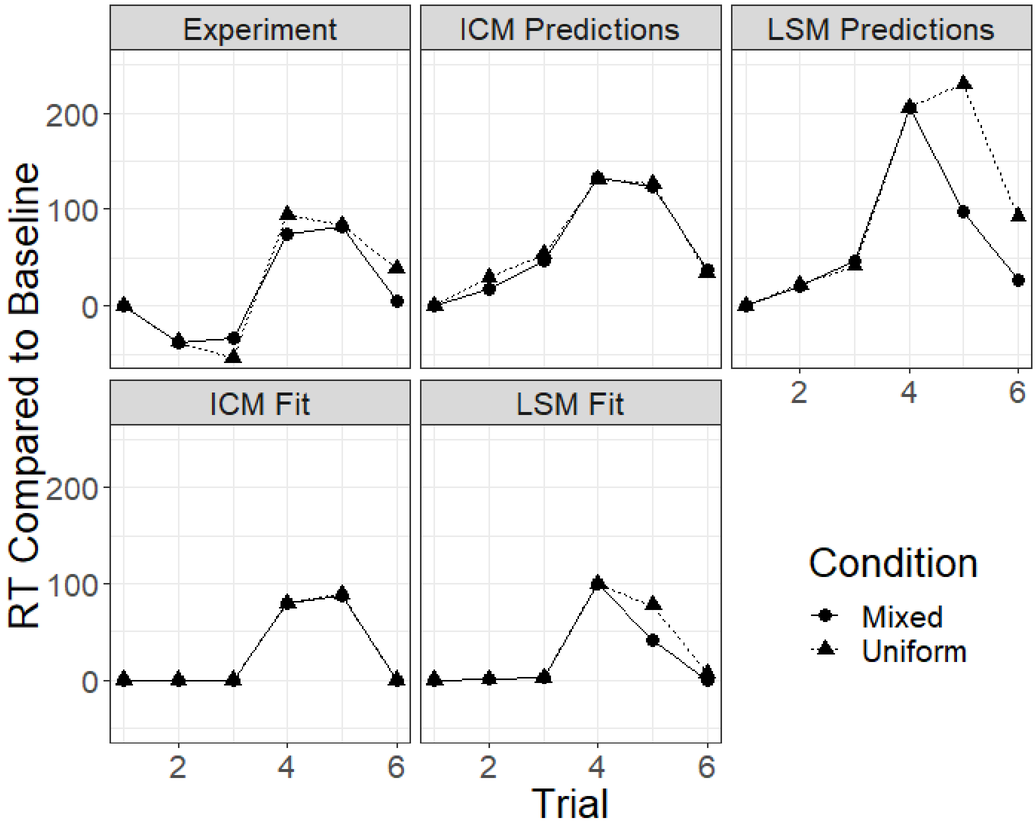


Figure 8. Naming Latency Results Based on Experiment One, Predictions and Model Fit. Results are graphed by *trial number within a Sub-Block* and *Sub-Block Type*. The top left panel shows the means of Experiment One. The middle and right panels on the top row show the predictions based on the ICM and LSM respectively. The bottom panels show overall fit for the ICM and LSM. Baseline naming latency is equal to the mean naming latency of Trial One of a Sub-Block.

Analyzing the Computational Predictions, Data and Model Fit

Examining A Priori Predictions to the Data. In order to assess how well the models were able to predict the experimental data, the trial by sub-block predictions made by the LSM, ICM computational models, and experimental data are given in Figure 8 (top panels). Visually inspecting the Figure 8, it seems the ICM computational model fits the data better on trials five and six than does the LSM computational model.

Fitting the Models to the Data. As can be seen in Figure 8, *a priori*, the ICM computational model does slightly better than does the LSM at minimizing the total error, especially for uniform sub-blocks. However, the degrees of freedom in this case are small, making it difficult to statistically assess whether one model fits the data better than the other. Additionally, these predictions were made before data were collected. It is possible that by adjusting the parameters, and with more observations, the LSM computational model might perform better than the ICM computational model. In order to test this, means of the overall data, and means for each participant in Experiment One were calculated by trial and sub-block type. Both models used *random search* with 1000 iterations to simulate reaction times in R for overall data and for each participant. Random search has been shown to be an efficient way to fit a model to a dataset (see Bergstra & Bengio, 2012). For each iteration, parameters of interest were allowed to vary randomly, results were compared to data, and the root mean square error (RMSE) was measured. The iteration with the lowest RMSE was chosen as the "best fit," and the parameter values were recorded.

Each model was allowed to vary three parameters at random based on a uniform distribution. The range of a parameter's variation was determined by examining each of their individual effects on naming latencies. A more thorough explanation of how each parameter affects simulated reaction times can be found in Appendix A. For example, a language strength parameter larger than five allows for very large within-language interference effects. Having it equal to one gives small interference effects. The parameters were allowed to vary over a range that was even larger than one might reasonably think *a priori* to ensure the parameters were not being too constrained. For the ICM, the three parameters allowed to vary were the competition parameter (*V;* allowed to vary from 0.51-0.75), language strength parameters (*L;* allowed to vary from 1 to 10) and inhibition parameter (*Y;* allowed to vary from 1 to 10). For the LSM, this was the competition parameter (*V;* allowed to vary from 0.51-0.60; there are fewer possible distractors in the LSM, so 0.60 is comparable to 0.75), the language strength parameter on stay trials (L_{stay}; allowed to vary from 1 to 10), and language strength parameter on switch trials (L_{switch};; allowed to vary from 3 to 30). It should be noted that the language switch parameter on switch trials for the LSM functions in a similar manner as the inhibition parameter for the ICM since both determine switch costs.

For the overall data, the iteration with the lowest RMSE (out of 1000 total iterations) was chosen as the best fit, with each computation having seven degrees of freedom (10 observations representing average naming latencies on trials two through six within a sub-block; three parameters were free to vary. For the LSM, overall fit was good for mixed sub-blocks, RMSE = 36.37, χ^2= 7.84, p=0.16 and uniform sub-blocks, χ^2= 2.02, p=0.85. For the ICM, overall fit was good for mixed sub-blocks, RMSE = 21.48, χ^2= 5.94, p=0.31 and for uniform sub-blocks, χ^2= 1.55, p=0.87. Results are plotted in the bottom panels of Figure 8.

For each participant, the iteration with the lowest RMSE (out of 1000 total iterations) was chosen, with each computation having seven degrees of freedom. Results are shown in Figures 9 and 10. The 86 RMSE values[5] associated with the participants were then used to assess which model better fit the data. For mixed and uniform blocks, RMSE from the LSM on each trial was compared to RMSE from the ICM in a Bayesian paired-samples t-test, and a Bayes factor was calculated. Bayes factor compares the likelihood of two hypotheses: the null and the alternative. In this case, the null hypothesis is that the two computational models have the same average participant RMSE. The alternative hypothesis is that one of the model's average RMSE is less than the other. A Bayes factor greater than one favors the alternative hypothesis, whereas a

[5] Each of the 43 participants had an RMSE value associated with a mixed and uniform sub-block

Bayes factor less than one favors the null hypothesis. On mixed trials, $BF_{10} = 0.17$, indicating that both models performed equally well. On these trials, average RMSE was 70.09 for the ICM, whereas the LSM had an RMSE of 69.76. However, on uniform trials, $BF_{10} = 1739.71$, indicating that the ICM outperformed the LSM. On these trials, average RMSE was of 81.11 for the ICM, whereas average RMSE was 92.83ms for the LSM. Recall that the LSM predicted uniform blocks to have longer naming latencies after a language switch. The ICM predicts mixed and uniform bocks to behave similarly. The fact that the ICM, which predicts the same naming latencies in mixed and uniform blocks, fits the data better than the LSM, which is allowed to vary based on sub-block type, is not trivial. It supports the idea that inhibition is used during repeated language switching, and may be an important mechanism in bilingual language control.

It should be noted that the models fail on trials where facilitation is observed from one trial to the next (e.g., Participants 2, 3, 4 in Figures 9 and 10). The models do better when there is interference. This is due to the competitive nature of the models. A target word is selected only after it reaches an activation level that is some ratio of the sum of the distractors' activation levels. The ratio is the competition parameter (V). By default, V is usually equal to 0.50 *at the beginning of any given trial*. Any value for V that is less than or equal to 0.50 would mean that the target is chosen without any input from the semantic network (i.e., t=0). For those participants who show a lot of facilitation, the way the models minimize error is to assume no competition and set V to some value less than 0.50. This results in no change in reaction times on stay trials, and reflects the fact that the computational models *cannot* simulate facilitation.

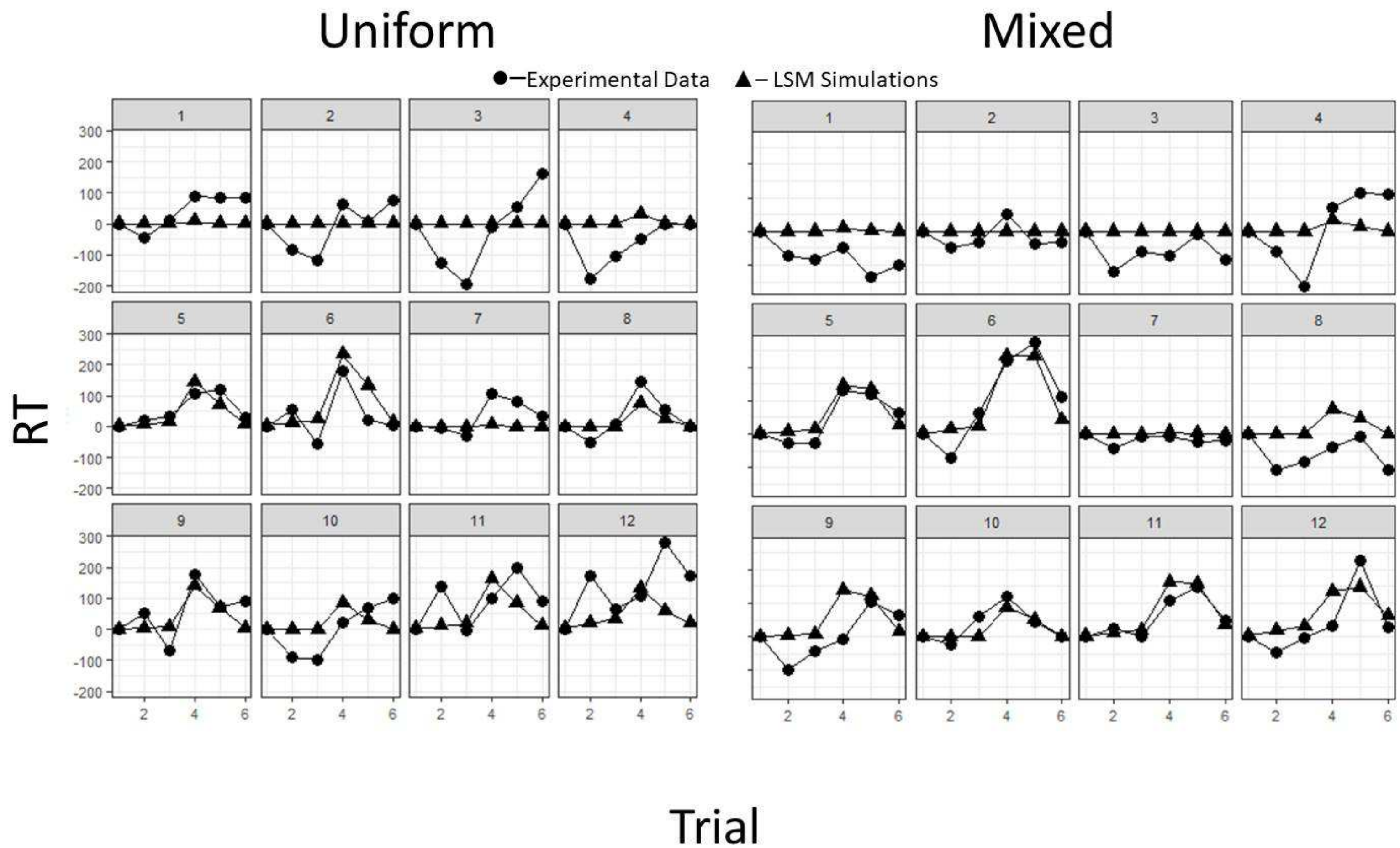


Figure 9. Graphs of Fit for the LSM Computational Model of Twelve Participants. Fits for uniform blocks are shown on the left, and mixed blocks on the right. The language strength parameters on stay and switch trials (*L*) and competition parameter (*V*) were allowed to change.

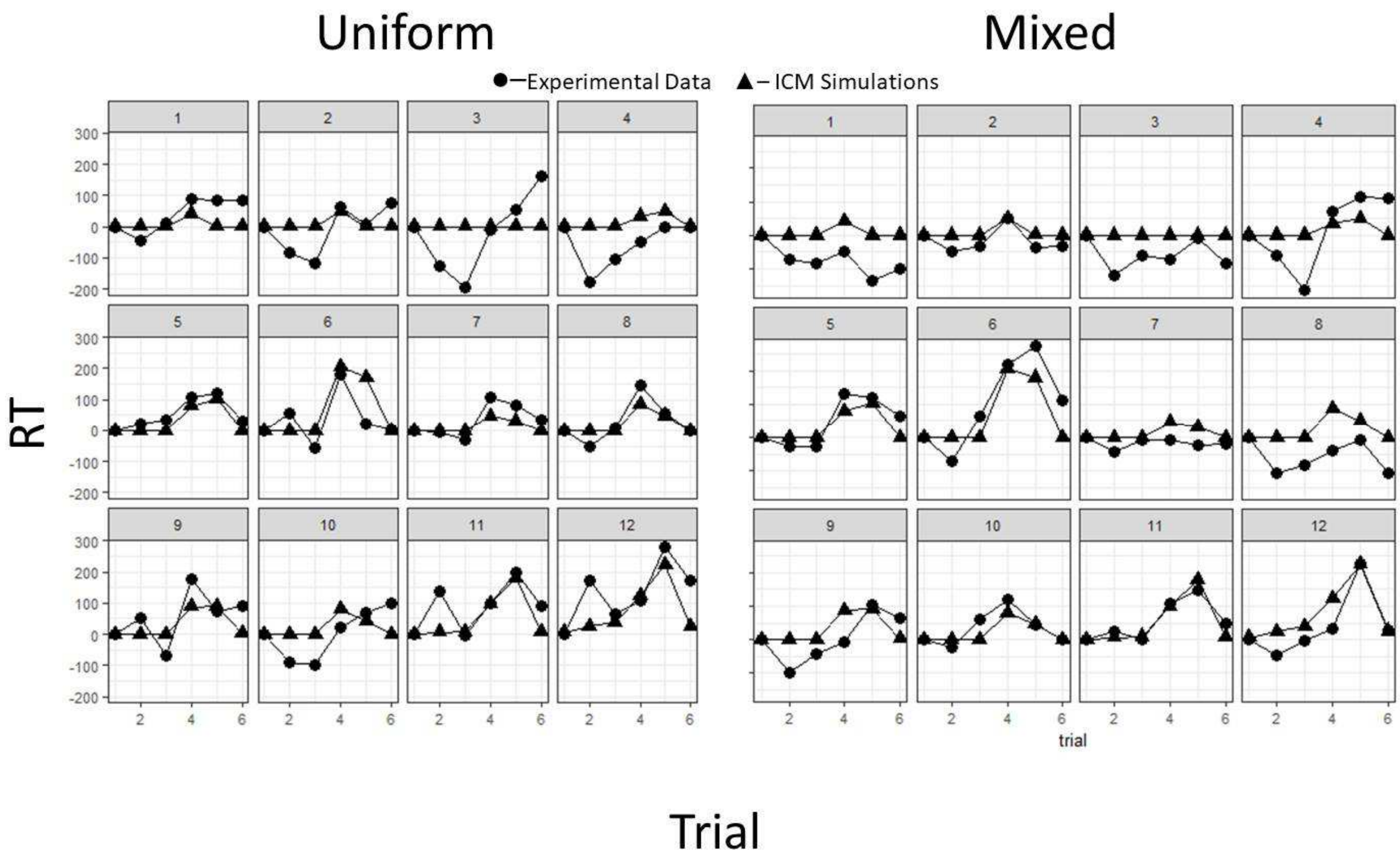


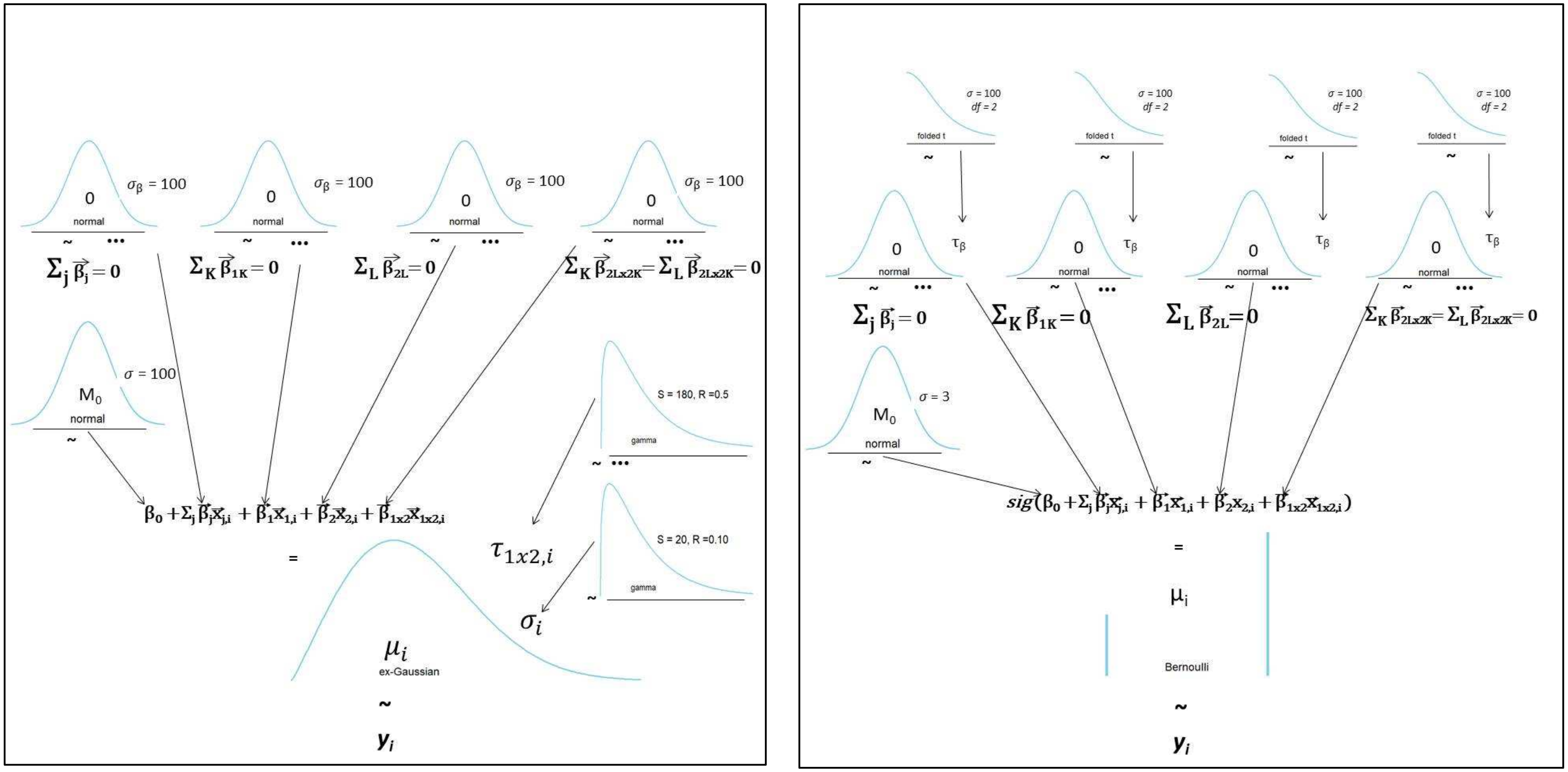
Figure 10. Graphs of Fit for the ICM Computational Model of Twelve Participants. The language strength parameter (L), the inhibition parameter (h) and competition parameter (V) were allowed to change. Fits for uniform blocks are shown on the left, and mixed blocks on the right.

Overview of Statistical Analyses

Statistics for this experiment were conducted using two Bayesian Hierarchical Models. The first Bayesian model examined reaction times, while the second assessed accuracy of the responses. Bayesian models require transparency, especially when setting up priors. For this reason, I have included a brief overview of the models and their priors. Both Bayesian models were implemented in RJAGS in R (Plummer, 2013)

The model assumed that naming latencies came from an ex-Gaussian distribution. An ex-Gaussian distribution is a convolution of a Gaussian and exponential distributions. The Gaussian portion represents the faster responses, and the exponential portion represents the slower responses (i.e., the tail of the distribution). It has three parameters: mu (μ), sigma (σ) and tau (τ) (see Luce, 1986). μ and σ represent the mean and standard deviation of the Gaussian portion, while τ is a measure of both the variance and mean of the exponential portion. The mean of the whole distribution is equal to μ plus τ. μ was allowed to vary based on fixed effects and random effects. Separate τ values were estimated for each combination of levels for each independent variable. Assuming that the data comes from an ex-Gaussian distribution makes it unnecessary to throw out naming latencies because they are too long. This assumes that longer responses are important, and (like shorter responses) contain valuable information. Recall that if a participant failed to respond before 3000ms, this was considered a timeout. This prevented extreme outliers from influencing the analyses. For a diagram of the Bayesian model, see Figure 11a.

Accuracy data for each analysis were input into another Bayesian hierarchal model. This model assumed each response comes from a Bernoulli distribution. A Bernoulli distribution is a special type of binomial distribution that estimates the probability of a successful, single trial. See Figure 11b for a diagram of this model.



a **b**

Figure 11. A diagram of the hierarchical dependencies of the Bayesian Hierarchical Models. Ellipses ("…") indicate that a parameter was allowed to vary for all levels of a variable. y_i represents a participant's response, which is assumed to come from a raw distribution of responses. A linear model is applied to the mean of the raw distribution in order to estimate deflections (β). Arrows connect the priors or hyper-priors to their respective parameters. The subscript *j* represents random effects. Numbered subscripts represent fixed effects. The panel on the left (**a**) shows the model used for analyzing naming latencies. The panel on the right **(b)** shows the model used for analyzing accuracy.

To interpret Figure 11a and 12b, one starts at the bottom and works their way up. The first symbol is y_i, and it represents a single score (e.g., reaction time). The subscript *i*, represents the *i*th score of the dataset. A tilde (~) shows the probability distribution from which a parameter or observed value (e.g., *y*) comes from. For example, in Figure 10a, the tilde above *y* signifies that scores come from an ex-Gaussian distribution [i.e., $y_i \sim \text{exGaussian}(\mu, \sigma, \tau)$]. Each distribution is represented visually, and central tendency parameters are shown inside the curve of the distribution (e.g., μ) while variance parameters are shown outside it (e.g., σ, τ). Equal signs show a deterministic relationship between two objects in the figure. For example, a linear model is fitted to μ in both the reaction time and accuracy models. β_0 represents the baseline (i.e, grand mean), while $\vec{\beta}\vec{x}$ represents the dot product between two vectors: a nominal predictor $\vec{x}$ and a deflection estimate β (i.e., how much a particular fixed or random effect is different from baseline). Since there is more than one nominal predictor, the subscript *j* represents the *j*th random intercept, while numerical subscripts indicate fixed effects. The subscripts *K* and *L* represent the levels of the nominal (fixed) predictors $\vec{x}_1$ and $\vec{x}_2$ respectively. Moving up the diagrams, one sees arrows pointing toward parameters (e.g., toward deflections estimates [β], variance estimates etc.). These indicate that there is a prior associated with the estimate, and is represented by an equation. For example, prior beliefs indicate that $\vec{\beta}_1$ in Figure 11a comes from a normal distribution with a mean of zero milliseconds and standard deviation of 100ms [$\vec{\beta} \sim N(0, 100)$]. In other words, it is assumed that the first fixed effect has no overall effect on the baseline. However, it is also *uninformed,* meaning the standard deviation is large (i.e., 100ms), and therefore the overall effect could be large.

Note that the priors for variance estimates require some care. For example, the hyper-prior for σ_i in Figure 11a is represented by a gamma distribution. A gamma distribution has two parameters: shape and rate, which determine the mean (i.e., mean = shape/rate) and standard deviation (sd = √shape/rate) of the gamma distribution. Based on previous bilingual research done in the lab, σ_i tends to be around 100-200 for participants in my studies. I then set up the prior distribution to have a mean of about 200, but a large standard deviation. Having a shape parameter (S) of 20 and rate parameter (R) of 0.10 accomplishes this. Priors on τ were also informed by previous research. Notice that τ has the subscript 1x2, meaning that it was allowed to change based on the levels of the fixed effects. In Figure 10b, priors on variance estimates also had hyper-priors. These hyper-priors were suggested by Kruschke, (2014).

Bayesian models have several advantages over traditional approaches. First, it allows for a straightforward interpretation of the results. Instead of giving *p*-values, the model estimates a grand mean for the combined data. It also estimates how each level of an independent variable (i.e., main effect) and combination of levels (i.e., interactions) are different from the grand mean in milliseconds. The estimates for how much a particular level of an independent variable (or combination of levels) are different from the grand mean are called deflections. Secondly, it provides the probability of a hypothesis (e.g., that two means are different) given the data and the model's assumptions. This probability is represented by taking samples from the resulting posterior distribution to create highest density intervals (HDI). If 95% of the highest density of a deflection estimate (or mean difference) of an independent variable does not contain zero, then one is 95% confident that the independent variable affects the dependent variable. Thirdly, the model is flexible, allowing for multiple analyses. Deflection estimates taken from posterior distributions can be combined in several ways. If analyzing an ordinal independent variable, one could treat each ordinal position as a separate condition. Alternatively, one can theoretically average the deflection estimates to find an average slope for the variable. Fourth, Bayesian models more easily deal with outliers. The final posterior distribution can be thought of as the combination of the prior distributions and the data (i.e., the likelihood). The prior distributions helps ensure that outliers do not disproportionally affect the analysis, which results in a "shrinkage" of parameter estimates. An added benefit to this is that it helps control for type I errors. Finally, these better model reaction time data without needing to transform it (e.g., log transformation), which can render the data uninterpretable.

In addition, there are a couple of steps needed for MCMC sampling in order for Bayesian models to be accurate. The first is do an initial sampling phase (i.e., adaptation) to maximize the model's efficiency. 10,000 iterations were used during this phase. The next is to "burn in" the model. As the model starts sampling, it may not yet be optimized around the true posterior distribution. The burn in phase allows the model to start sampling without saving the results. 10,000 iterations were discarded during this phase. Finally, the model can start sampling. Three *chains* were used in the reaction time model, and ten chains in the accuracy model. Each chain represents a sample of the posterior distribution, and they are used to ensure that the model converges. 10,000 samples were taken for each chain.

Trials 1-3.

Naming Latency Analysis. In order to answer question two (whether there is competition within a language; p.34), trials one through three were analyzed using the reaction time Bayesian model. *Trial number* (*one, two, three*) and *language* (*L1, L2*) were input as fixed effects. Language of the stimulus (*English, Spanish*) and stimulus were input as random intercepts. Because the Bayesian model assumes an underlying ex-Gaussian distribution, no trials were thrown out due to being too long. In other words, the Bayesian model assumes a long tail of responses. Only trials that were less than 500ms were removed. 1237 trials (7.8%) were excluded from the analysis due to participant error. Of these, 654 (4.1%) were due to timeouts, 151 (0.9%) were intrusion errors, 368 (2.3%) were incorrect but semantically related/correct language responses, and 64 (<0.5%) were other errors (e.g., non-semantically related words, non-words, coughs etc.).

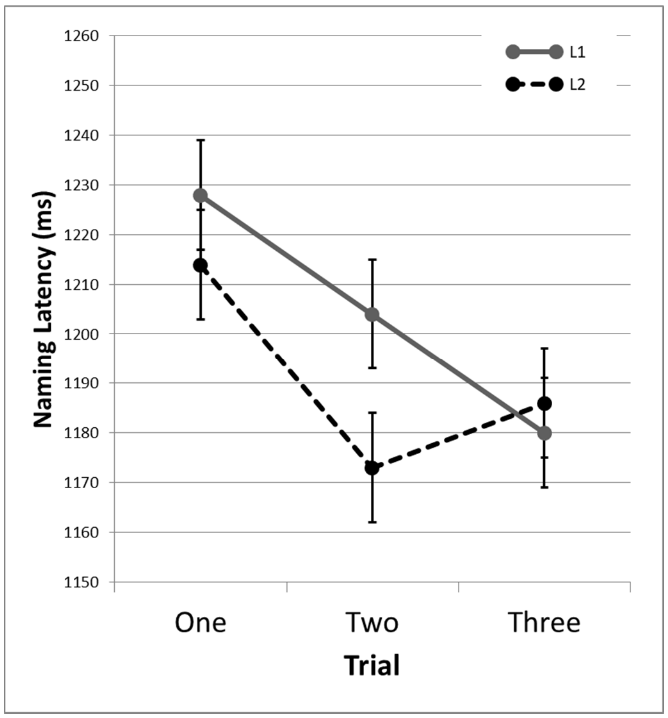


Figure 12. Mean naming latency estimates by language and trial (1-3). Error bars represent 95% HDI for each mean, based on the Bayesian model.

Results are summarized in Table 4. A credible main effect of language was found. L1 trials were 13.21ms slower than L2 trials, 95% HDI [6.25, 20.35]. Additionally, a credible main effect of trial type was found. The first trials in a sub-block were 33.11ms slower than the second trials, 95% HDI [15.55, 47.67], and 38.45ms slower than the third trials, 95% HDI [24.08, 55.65]. However, the second and third trials were not credibly different, 95% HDI [-18.93, 10.53]. See Figure 12 for a representation of the results.

These main effects are qualified by a language by trial order interaction. For L1 trials, there is roughly equal facilitation from the first to second trials in a sub-block (-24.49ms, 95% HDI [-48.77, -2.89]) compared to the second and third trials (-23.90, 95% HDI [-45.51, -2.57]). However, for L2 trials, there is a relatively large facilitation effect from the first to second trials in a sub-block (-41.73ms, 95% HDI [-63.47, -19.30]), but there is no credible difference between the second and third trials in a sub-block (13.22, 95% HDI [-7.52, 13.50]).

In order to interpret Table 4 (and the other tables that give the results of the Bayesian models in this dissertation), one simply has to add all deflection estimates of interest to the grand mean in order to calculate the individual condition mean. The deflection estimates are interpreted similarly to between group deviations in an ANOVA model. The grand mean is the center of the data, and the deflections estimate how much the mean of particular level is different from the grand mean (note: if there are only two levels of a variable, then the deflection estimates must be symmetrical). For example, in order to estimate the average naming latency of stimuli named in L1 using Table 4, one simply adds the deflection estimate of the corresponding "L1" row (i.e., 6.23ms) to the grand mean estimate (1197.93) to get the 1204.16ms. If one wants to estimate the mean naming latency of stimuli named in L1 on Trial One, one must add the L1 (6.23ms), Trial One (23.89ms) and L1 One (0.58ms) rows to the grand mean (1197.93ms) to get the cell mean of 1228.63ms.

Because facilitation was found on the first three trials of a sub-block, the data were analyzed again to rule out possible phonological facilitation effects. Even though phonologically related neighbors within a language were not presented one after another, it may have been possible that words were phonologically primed by words in the non-target language from the previous trial. To test this, trials were thrown out if its stimulus name had the same onset as the stimulus name in the other language on the previous trial. Results were similar to the analysis presented in Table 4. In other words, cross-language phonological priming is not responsible for the facilitation found in this experiment.

Table 4. *Naming Latency Results on Trials 1-3 based on the Bayesian Model*

Source	Level	Mean (*SE*)	BHM Mean Estimate	Deflection Estimate (ms)	95% HDI	
					Lower	Upper
Grand Mean		1195 (3.44)	1197.93	*NA*	*NA*	*NA*
Language	L1	1201 (4.79)	1204.16	6.23*	0.12	12.64
	L2	1189 (4.94)	1191.7	-6.23*	-12.64	-0.12
Trial	One	1222 (6.35)	1221.82	23.89*	14.07	33.73
	Two	1185 (5.79)	1188.75	-9.18*	-17.93	-0.67
	Three	1181 (5.77)	1183.28	-14.65*	-23.43	-6.02
Trial by Language	L1 One	1228 (8.79)	1228.63	0.58	-8.55	9.41
	L1 Two	1203 (8.11)	1204.12	9.14	-0.11	18.09
	L1 Three	1175 (8.01)	1180.13	-9.38*	-18.39	-0.86
	L2 One	1203 (8.11)	1215.01	-0.58	-9.41	8.55
	L2 Two	1169 (8.26)	1173.38	-9.14	-18.09	0.11
	L2 Three	1186 (8.31)	1186.43	9.38*	0.86	18.39

*A credible deflection at a 95% HDI was found

Accuracy Analysis. See Table 5 for a summary of the results. The Bayesian model used for the accuracy analysis was used. Each trial was coded either 1 or 0 (correct, incorrect) based on the participant's response. The analysis had the same fixed and random effects that the RT Bayesian model had when analyzing Trials One-Three. L1 words were named with 1.4% more accuracy than L2 words, 95% HDI [.11, 4.7]. Although accuracy somewhat increased trial by trial, trial number did not have a credible effect on accuracy. There was not a credible interaction between the two variables.

Table 5. *Accuracy Results on Trials 1-3 based on the Bayesian Model*

Source	Level	Mean	BHM Mean Estimate	Deflection Estimate (%)	95% HDI	
					Lower	Upper
Grand Mean		92.3	92.07	*NA*	*NA*	*NA*
Language	L1	93.0	92.62	0.55*	0.09	2.06
	L2	91.8	91.52	-0.55*	-2.06	-0.09
Trial	One	91.7	91.63	-0.44	-1.94	0.12
	Two	92.3	92.01	-0.06	-1.07	0.93
	Three	92.9	92.60	0.53	-0.04	2.09
Language x Trial	L1 One	92.4	92.12	-0.06	-1.19	0.94
	L1 Two	92.6	92.46	-0.10	-1.29	0.67
	L1 Three	94.0	93.29	0.14	-0.62	1.24
	L2 One	91.0	91.14	0.06	-0.94	1.19
	L2 Two	92.1	91.56	0.10	-0.67	1.29
	L2 Three	92.0	91.91	-0.14	-1.24	0.62

*A credible deflection at a 95% HDI was found

Trial 5 Results

Naming Latency Analysis. Recall that the ICM predicts no difference between sub-blocks on Trial 5, whereas the LSM predicts uniform sub-blocks to have longer naming latencies than mixed sub-blocks. In order to test this (i.e., whether spreading activation is eliminated after a language switch; p.34), each participant's naming latency data on trial five of each sub-block were input into the RT Bayesian mixed effects model as the dependent variable. Language (*L1, L2*) and sub-block type (*mixed, uniform*) were input as fixed effects. Intercepts were allowed to vary according to participant, stimulus and language of the stimulus (*Spanish, English*). 527 trials (9.9%) were excluded from the analysis due to participant error. Of these, 235 (4.5%) were due to timeouts, 134 (2.5%) were intrusion errors (i.e., wrong language), 130 (2.4%) were incorrect but semantically related/correct language responses, and 28 (<1%) were other errors (e.g., non-semantically related words, non-words, coughs etc.).

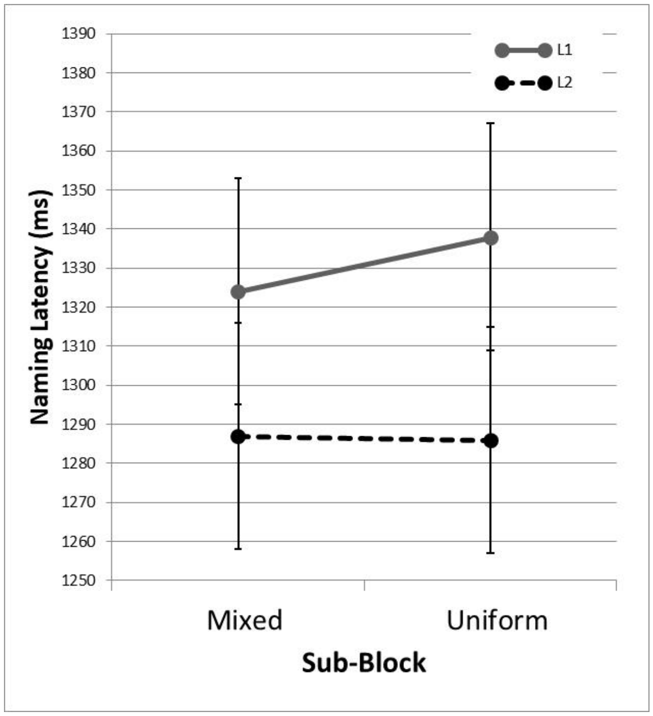


Figure 13. Mean naming latency estimates by language and sub-block on trial 5. Error bars represent 95% HDI (roughly ±2 *SE*) for each mean, based on the Bayesian model.

Table 6. *Naming Latency Results on Trial 5 based on the Bayesian Model*

Source	Level	Mean (*SE*)	BHM Mean Estimate	Deflection Estimate (ms)	95% HDI	
					Lower	Upper
Grand Mean		1306 (6.44)	1309.00	*NA*	1295.46	1322.26
Language	L1	1329 (9.03)	1331.29	22.29*	9.29	36.41
	L2	1283 (9.17)	1286.71	-22.29*	-36.41	-9.29
Block Type	Mixed	1303 (9.02)	1305.82	-3.18	-16.59	9.91
	Uniform	1309 (9.21)	1312.18	3.18	-9.91	16.59
Language x Block	L1 Mixed	1321 (12.55)	1324.35	-3.76	-17.09	10.31
	L1 Uniform	1337 (13.01)	1338.23	3.76	-10.31	17.09
	L2 Mixed	1284 (12.94)	1287.29	3.76	-10.31	17.09
	L2 Uniform	1281 (12.99)	1286.13	-3.76	-17.09	10.31

Note: The means and standard errors are descriptive statistics. Deflections Estimates are from the Bayesian Model.
*A credible deflection at a 95% HDI was found

Results of Trial 5 are in Figure 13 and Table 6. Trial 5 was a switch trial, and consistent with previous findings, there was a main effect of language. L1 trials were 44.58ms slower than L2 trials, 95% HDI [19.4, 46.8]. Type of block (*mixed, uniform*) did not credibly affect reaction times. Neither was there an interaction between block type and language. Thus, spreading activation does seem to be eliminated after a language switch, supporting the ICM.

Table 7. *Accuracy Results on Trial 5 based on the Accuracy Bayesian Model*

Source	Level	Mean	BHM Mean Estimate	Deflection Estimate (%)	95% HDI	
					Lower	Upper
Grand Mean		90.0	90.2	*NA*	*NA*	*NA*
Language	L1	90.6	90.7	0.5	-0.2	1.3
	L2	89.4	89.7	-0.5	-1.3	0.2
Block Type	Mixed	90.1	90.4	0.2	-0.5	1.1
	Uniform	89.9	90.0	-0.2	-1.1	0.5
Language x Block	L1 Mixed	91.7	91.5	0.3	-0.2	1.1
	L1 Uniform	89.7	90.1	-0.3	-1.1	0.2
	L2 Mixed	88.6	89.6	-0.3	-1.1	0.2
	L2 Uniform	90.2	89.9	0.3	-0.2	1.1

Accuracy Analysis. In order to assess whether language (*L1, L2*) or trial type (*mixed, uniform*) affected naming accuracy, each trial was coded either 1 or 0 (correct, incorrect) based on the participant's response. Similar to the naming latency analysis, language (*L1, L2*) and sub-block type (*mixed, uniform*) were input as fixed effects. Intercepts were allowed to vary according to participant, stimulus and language of the stimulus (*Spanish, English*). The grand mean represents the probability of a successful response, and the deflections for each condition represent how much the probability changes. There were no main effects or interactions. See Table 7 for a summary of the results.

Trial 6 Results

Naming Latency Analysis. In order to answer question one (whether spreading activation is eliminated after a language switch; p.34), the same Bayesian model used for Trial 5 data was used to analyze naming latencies for trial 6 data. Recall, the ICM predicts no difference between uniform and mixed sub-blocks. The LSM predicts a large difference between uniform and mixed sub-blocks. 449 trials (9.9%) were excluded from the analysis due to participant error. Of these, 232 (4.3%) were due to timeouts, 72 (1.3%) were intrusion errors, 120 (2.3%) were incorrect but semantically related/correct language responses, and 25 (<1%) were other errors (e.g., non-semantically related words, non-words, coughs etc.).The data were analyzed twice: once where trial six responses were thrown out if trial five responses were incorrect, and once where trial six responses were included if trial five responses were incorrect. Both gave similar results. The latter analysis is presented here.

See Table 8 and Figure 14 for a summary of the results. There was a credible main effect of language (*L1, L2*). L2 stimuli were named 30.8ms faster than L1 stimuli, 95% HDI [-54.83, -5.58]. There was a credible main effect for type of block (*mixed, uniform*). Uniform blocks were 38.30ms slower than mixed blocks, 95% HDI [-61.7, -14.7]. There was no credible interaction between block type and language. Although the LSM predicted naming latencies to be longer for uniform sub-blocks compared to mixed sub-blocks, the difference was smaller than predicted based on the computational model.

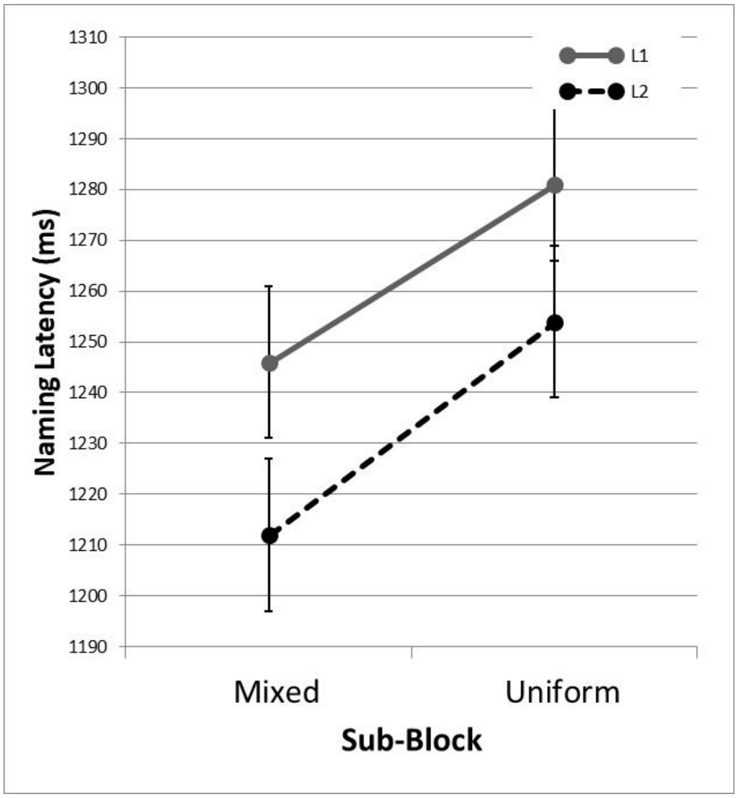


Figure 14. Mean naming latency estimates by language and sub-block on trial 6. Error bars represent 80% HDI for each mean, based on the Bayesian model.

Table 8. *Naming Latency Results on Trial 6 based on the Bayesian Model*

Source	Level	Mean (*SE*)	BHM Mean Estimate	Deflection Estimate (ms)	95% HDI	
					Lower	Upper
Grand Mean		1246 (6.03)	1245.24	*NA*	1232.90	1257.66
Language	L1	1261 (8.50)	1260.66	15.42*	2.79	27.41
	L2	1230 (8.54)	1229.82	-15.42*	-27.41	-2.79
Block Type	Mixed	1226 (8.35)	1226.21	-19.03*	-30.77	-7.26
	Uniform	1265 (8.68)	1264.27	19.03*	0.17	12.65
Language x Block	L1 Mixed	1244 (11.80)	1243.47	1.84	-10.43	13.33
	L1 Uniform	1279 (12.22)	1277.85	-1.84	-13.33	10.43
	L2 Mixed	1209 (11.80)	1208.95	-1.84	-13.33	10.43
	L2 Uniform	1251 (12.33)	1250.69	1.84	-10.43	13.33

Note: The means and standard errors are descriptive statistics. Deflections Estimates are from the Bayesian Model.
*A credible deflection at a 95% HDI was found

Accuracy Analysis. See Table 9 for a summary of the results based on the Bayesian model. The data were analyzed the same way as in trial 5. L1 trials were named with 2.0% more accuracy than L2 trials, 95% HDI (0.0, 5.0]. There was no main effect of sub-block type, nor was there an interaction between language and sub-block type.

Table 9. *Accuracy Results on Trial 6 based on the Bayesian Model*

Source	Level	Mean	BHM Mean Estimate	Deflection Estimate (%)	95% HDI Lower	95% HDI Upper
Grand Mean		91.5	91.76		*NA*	*NA*
Language	L1	92.5	93.30	1.0*	0.1	2.9
	L2	90.5	91.28	-1.0*	-2.9	-.01
Block Type	Mixed	92.2	92.29	0.3	-0.2	2.5
	Uniform	90.8	91.23	-0.3	-2.5	0.2
Language x Block	L1 Mixed	93.4	93.39	0.0	-0.6	0.4
	L1 Uniform	91.2	92.14	0.0	-0.4	0.6
	L2 Mixed	91.1	91.20	0.0	-0.4	0.6
	L2 Uniform	89.9	90.34	0.0	-0.6	0.4

*A credible deflection at a 95% HDI was found

Discussion

In this experiment, I tested whether switching languages eliminates priming effects. This was done to test the predictions of two prominent theories of bilingual language control: the inhibitory control model (ICM) and lexical selection mechanism model (LSM). Participants named picture stimuli in sub-blocks. Sub-blocks consisted of six trials, all with the same switching order (stay, stay, stay, switch, switch, stay), and there were two types: mixed and uniform. Uniform sub-blocks consisted of stimuli from the same semantic category. Mixed sub-blocks changed semantic category on trial five.

The results generally support the predictions made by the ICM. The ICM predicts that language switching should "lead to the abolition of both cross-language and within-language competitor priming" (Green 1998a). On trial five, there was no credible difference in naming latencies between mixed sub-blocks and uniform sub-blocks. Additionally, there was no difference in accuracy between mixed and uniform sub-blocks. Whatever effect spreading activation had on the previous trials was eliminated on trial five.

There is one piece of evidence that favors the LSM, however. On trial six, uniform blocks were slower than mixed blocks. In light of this piece of evidence, how might one resolve the difference found between the two trials? Arguing from the LSM point of view, one might propose that lexical selection within a language and the language switching mechanism operate in parallel. On trial five, the target word becomes activated at the same time as the lexical selection mechanism switches language. Instead of summing the language switch cost and within language interference cost, one would only need to take into account the switch cost, assuming it is the one that takes the most time. Because of this, there would be no difference between mixed and uniform sub-blocks on switch trials. However, on stay trials (i.e., trial six of the experiment), switch costs are irrelevant, which is why on trial six, stimuli in mixed sub-blocks were faster than in uniform sub-blocks.

There are two problems with this argument. The first is that *facilitation was found in trials one through three*. Recall that the first three trials in a sub-block were all stay trials. Why was facilitation found for these three trials, but on trial six naming latencies were slower for uniform sub-blocks compared to mixed ones? If residual, spreading activation facilitates naming from one trial to the next on the first three trials, it should also facilitate naming during uniform sub-blocks on trials five and six compared to mixed sub-blocks. It would seem that there are two separate mechanisms affecting the results. The first is spreading activation. This affects trials one through three, creating facilitation from one trial to the next. The second is incremental learning, which slows naming on a trial six from uniform sub-blocks more than it slows naming on a trial six from mixed sub-blocks. The reason is that on trial 6 of a uniform sub-block, it is guaranteed that all the target stimulus' semantic neighbors have been named. The stimulus' lexico-semantic connections are severely weakened by naming semantic neighbors from the first five trials of the sub-block. However, it is not guaranteed that all of a stimulus' semantic neighbors have been named on a trial six in a mixed sub-block. On average, only three of them would have been named. Trial six stimuli from a mixed sub-block get named somewhat faster than trial six stimuli from a uniform sub-block because the mixed sub-block stimulus' lexico-semantic connections have not been weakened as much as they might be in a uniform block.

Secondly, the difference in naming latencies between the sub-block types was not as great as would be expected. The LSM computational model in chapter two predicted that there would be a very large difference between the mixed and uniform sub-blocks on trial six. These two issues make the LSM a less desirable explanation than the ICM. Additionally, when fitting the models to the participant data, the ICM had less error than the LSM.

Although inhibition seems to be important in controlling between language output, this experiment suggests that parts of the ICM need to be updated. The first is that words within a language do not compete for selection. The fact that facilitation was found for the first three trials of a sub-block is evidence of this. Implications of within –language facilitation for the ICM will be dealt with in the General Discussion (Chapter Five). The second is that incremental learning is also a factor in language control. However, inhibition does not seem to affect the process of learning incrementally because its effects were found on trial six after a language switch. This second conclusion is tentative. It is possible that the difference found between mixed and uniform sub-blocks on trial six was spurious. It was not expected a priori. Chapter four addresses this question specifically.

CHAPTER FOUR:

EXPERIMENT TWO – DOES LANGUAGE SWITCHING AFFECT CUMULATIVE SEMANTIC INTERFERENCE? A TEST FOR INCREMENTAL LEARNING

Experiment one found that priming effects were eliminated after a language switch. This supports the ICM over the LSM. However, Runnqvist et al. (2012) found that cumulative semantic interference was not reduced in the cyclical paradigm. They took this as evidence against the ICM. But, those results may indicate that language switching does not affect incremental learning effects. In order to test this, participants named semantically related neighbors, this time separated by filler trials, (i.e., the cyclical paradigm was used). If cumulative semantic interference is the result of a learning mechanism that is independent of semantic priming, then two predictions can be made. **(1)** Cumulative semantic interference should occur on both stay and switch trials: with each presentation of a semantic neighbor within a block, naming latency should increase 10-30ms (see Howard, Nickels, Coltheart, & Cole-Virtue, 2006; Navarrete, Del Prato, & Mahon, 2012; Navarrete, Mahon, & Caramazza, 2010). **(2)** The number of filler trials should not affect the rate at which CSI (inferred by naming latency) increases. If both those predictions hold, then this supports the idea that a learning mechanism may be responsible for CSI, not long-lasting residual activation. If true, CSI occurring after a language switch should not be taken as evidence against inhibition being used in language switching.

Method

Participants

45 English-Spanish speaking bilingual participants (66% female) were recruited through the USF psychology department participant pool. The same questionnaire used in Experiment One was given to participants in Experiment Two (see Appendix B), as well as the Multilingual Naming Test. One participant was excluded because they could not name more than 10% of the pictures in MINT. See Table 10 for a summary of participants' self-ratings of language proficiency and the results of the Multilingual Naming Test.

Table 10. *Participants' language proficiency in Experiment Two*

	Language	
Measure	L1	L2
Self-Ratings		
Speaking (out of 7)	6.61 (0.5)	6.09 (0.9)
Reading (out of 7)	6.48 (0.7)	6.18 (1.3)
Writing (out of 7)	6.30 (0.7)	6.02 (1.0)
Age of Acquisition	2.65 (3.3)	4.38 (5.7)
MINT (% correct)	89 (10)	73 (12)

Note: Means of each measure are given with standard deviations in parentheses

Stimuli

The same stimuli used in Experiment One were used in Experiment Two.

Apparatus

The same apparatus used in Experiment One was used in Experiment Two.

Procedure

The procedure in Experiment One was similar to that of Experiment Two with one major exception: Stimuli within a block were pseudorandomized so that at least one intervening trial separated semantically related stimuli. Because of this, the mixed/uniform distinction no longer applies.

Results

Incremental Learning Effects on RT during Switch and Stay Trials

In order to test Prediction One (p. 66), a Bayesian model that is similar to the models used for analyzing naming latencies in Experiment One was used to assess incremental learning effects in this experiment. Participant, stimulus, language (*L1*, *L2*) and language of the stimulus (*English, Spanish*) were input as random intercepts. Trial type (*stay*, *switch*) and ordinal presentation of a semantically related stimulus (*one* through *six*) were input as fixed effects. In order to determine ordinal position, the first presentation of a semantically-related stimulus for a given language was coded *one*, the second presentation was coded *two* and so forth. Note, that at least one non-semantically related stimulus (i.e., a filler trial) was shown between presentations. Also, filler trials were themselves coded *one* through *six* based on their ordinal position within a block. If the beginning of a block began with the following stimuli, *parakeet, gun, duck, harp,* parakeet would be coded *one*, gun would be coded *one,* duck would be coded *two,* and harp would be coded *one.* Additionally, the first time a word in Spanish was named (*e.g., pato* meaning *duck*), it was also coded as *one*, even if its translation was already named). 3116 trials (10.2%) were removed due to participant error. Of these, 1333 (4.4%) were due to timeouts, 627 (2.1%) were intrusion errors, 983 (3.2%) were incorrect but semantically related/correct language responses, and 173 (<0.6%) were other errors (e.g., non-semantically related words, non-words, coughs etc.).

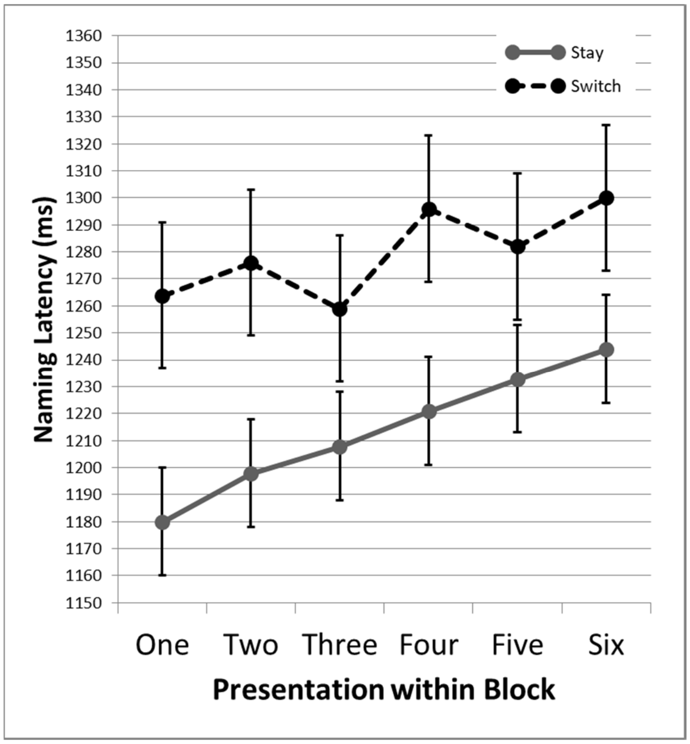


Figure 15. Naming Latencies by Trial Type and Presentation within Block. Error bars represent 95% HDI for each mean, based on the Bayesian model.

There was a main effect of ordinal presentation of a semantically related stimulus. Because ordinal presentation is measured on an ordinal scale, the Bayesian model can treat this variable as a quantitative variable in order to find the average slope of the variable. The slope of one ordinal presentation to the next ordinal presentation is defined as the difference between the respective mean estimates ($\bar{X}_2 - \bar{X}_1$, where $\bar{X}_i$ is the mean estimate for position i; $\bar{X}_i$ is estimated by sampling from the posterior distribution). This difference represents the change in reaction time from one ordinal presentation to the next. There are five slopes ($\bar{X}_2 - \bar{X}_1$, $\bar{X}_3 - \bar{X}_2$ etc.), which were averaged together. On average, naming latency credibly increased by 9.98ms for each presentation of a semantic neighbor, 95% HDI [5.46, 14.21]. Additionally, there was a main effect of trial type. Stay trials were named 65.60ms faster than switch trials, 95% HDI [-77.20, -55.01]. There was no interaction between language and presentation order. The results indicate that language switching had little to no effect on CSI effects, supporting Prediction One. See Table 11 and Figure 15 for a summary of the results.

Table 11. *Naming Latency Results by Ordinal Presentation and Trial Type based on the Bayesian Model*

Source	Level	Mean (*SE*)	BHM Mean Estimate	Deflection Estimate (ms)	95% HDI	
					Lower	Upper
Grand Mean		1240 (2.84)	1246.85	*NA*	*NA*	*NA*
Trial Type	Stay	1218 (3.47)	1214.05	-32.80*	-38.60	-27.26
	Switch	1284 (4.92)	1279.65	32.80*	27.26	38.60
Presentation Order	One	1201 (8.60)	1222.16	-24.69*	-39.24	-9.12
	Two	1229 (6.56)	1237.48	-9.37	-20.91	2.23
	Three	1227 (6.55)	1233.46	-13.39*	-24.49	-1.55
	Four	1248 (6.75)	1258.37	11.52	-0.40	23.54
	Five	1254 (6.75)	1257.25	10.40	-0.81	22.42
	Six	1264 (7.01)	1272.02	25.17*	12.82	37.43
	Average Slope			**9.98***	**5.26**	**14.21**
Trial Type x Presentation	Stay One	1176 (9.82)	1179.94	-9.42	-24.06	5.28
	Stay Two	1200 (8.11)	1198.56	-6.12	-18.37	5.31
	Stay Three	1212 (8.03)	1208.7	8.04	-3.85	19.34
	Stay Four	1222 (8.18)	1220.97	-4.60	-16.70	6.98
	Stay Five	1235 (8.55)	1232.78	8.33	-3.46	19.88
	Stay Six	1246 (8.42)	1243.35	4.13	-8.89	16.55
	Switch One	1272 (17.36)	1264.38	9.42	-5.31	24.05
	Switch Two	1339 (10.98)	1276.4	6.12	-5.31	18.37
	Switch Three	1246 (11.24	1258.22	-8.04	-19.34	3.85
	Switch Four	1254 (11.78)	1295.77	4.60	-6.98	16.70
	Switch Five	1288 (10.95)	1281.72	-8.33	19.88	3.46
	Switch Six	1308 (12.53)	1290.69	-4.13	-16.55	8.89

*A credible deflection at a 95% HDI was found. Bold type font indicates the average slope when treating *Presentation Order* as a continuous variable.

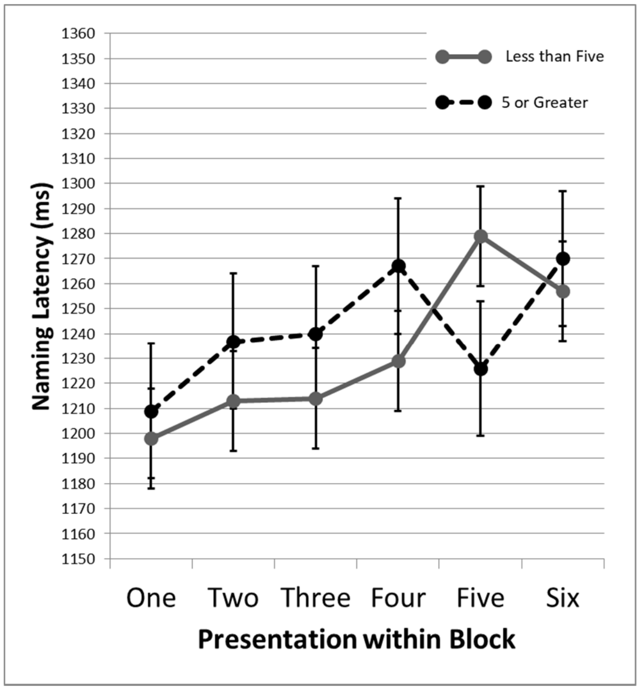


Figure 16. Naming Latency by Ordinal Presentation x Intervening Trials. Error Bars represent 95% HDI for each mean based on the Bayesian model.

Incremental Learning Effects and Number of Filler Trials

In order to test prediction two (p. 66), the Bayesian model was used to assess whether the number of filler trials between semantic presentations affected naming latency. Errors were removed from the analysis. Participant, stimulus, language (*L1*, *L2*) and language of the stimulus (*English, Spanish*) were input as random intercepts. Ordinal presentation of a semantically related stimulus (*one* through *six*) and number of filler trials were input as fixed effects. Half of the stimuli were separated from a semantic neighbor by five filler trials or less. Thus,number of filler trials was coded as “fewer than five” or “five or greater.” Overall, there was a main effect of ordinal presentation. With each presentation of a semantic neighbor, naming latency increased by 12.06ms, 95% HDI [7.21, 16.11]. Presentations with five or more filler trials were 8.88ms slower than trials with less than five filler trials, but the effect was not credible, 95% HDI [-19.46, 1.93]. Again, CSI effects were found.

Table 12. *Bayesian Model Deflection Estimates on Naming Latency Results by Ordinal Presentation x Number of Intervening Trials*

Source	Level	Mean (*SE*)	BHM Mean Estimate	Deflection Estimate (ms)	95% HDI	
					Lower	Upper
Grand Mean		1240 (2.84)	1240.86	*NA*	*NA*	*NA*
Intervening Trials	Less than 5	1237 (4.10)	1236.42	-4.44	-9.81	0.95
	5 or Greater	1243 (3.95)	1245.3	4.44	-0.95	9.81
Ordinal Presentation	One	1201 (8.60)	1208.11	-32.75*	-48.40	-16.80
	Two	1229 (6.56)	1229.52	-11.34*	-22.69*	-0.20*
	Three	1227 (6.55)	1232.23	-8.63	-20.17	2.50
	Four	1248 (6.75)	1252.58	11.72*	1.11	22.65
	Five	1254 (6.75)	1254.31	13.45*	2.71	24.92
	Six	1264 (7.01)	1268.42	27.56*	16.16	40.56
	Average Slope*			**12.06***	**7.21**	**16.11**
Trial Type x Presentation	<5 One	1174 (18.45)	1199.51	-4.16	-19.59	11.85
	<5 Two	1213 (9.37)	1216.38	-8.70	-19.77	2.41
	<5 Three	1214 (8.77)	1219.74	-8.05	-19.37	2.75
	<5 Four	1225 (9.11)	1234.4	-13.74	-25.10	-2.14
	<5 Five	1287 (9.93)	1284.98	35.11*	23.75	46.37
	<5 Six	1255 (9.55)	1263.71	-0.27	-12.45	11.48
	<5 Average Slope*		1259.75	**12.85***	**4.88**	**19.55**
	≥5 One	1206 (9.63)	1216.71	4.16	-11.85	19.59
	≥5 Two	1243 (9.15)	1242.66	8.70	-2.41	19.77
	≥5 Three	1243 (9.82)	1244.72	8.05	-2.75	19.37
	≥5 Four	1272 (9.97)	1270.76	13.74*	2.14	25.10
	≥5 Five	1221 (9.08)	1223.64	-35.11*	-46.37	-23.75
	≥5 Six	1276 (10.31)	1273.13	0.27	-11.48	12.45
	≥5 Average Slope*			**11.28***	**6.22**	**16.48**

Note: The means and standard errors are descriptive statistics. Deflections Estimates are from the Bayesian Model.
*A credible deflection or slope at a 95% HDI was found. Bold type font indicates the average slope of *Presentation Order*.

The critical question is whether CSI diminishes when the number of filler trials increases. In other words, is there an interaction between ordinal presentation and number of filler trials? When examining ordinal presentation as a categorical variable, there was a credible interaction between ordinal presentation and number of intervening trials. On the fourth presentation with fewer than five filler trials, mean naming latency was 13.74ms faster than average, 95% HDI [-25.09, -2.14]. However, on the fifth presentation, mean naming latency was 35.12ms slower than average, 95% HDI [32.74, 46.37]. The reverse was true for the fourth and fifth presentations that had five or more intervening trials. However, these results could be just statistical noise. When analyzing the model as if ordinal presentation were a continuous variable, the average slope with fewer than five intervening trials is 12.85ms per ordinal presentation, 95% HDI[4.88, 19.6], and it is nearly identical to the average slope of five or more trials, 11.35ms per ordinal presentation, 95% HDI [6.22, 16.48]. Critically, the difference between the slopes is only 1.40ms per presentation and is not credible, 95% HDI [-7.72, 9.89]. The results indicate that the number of filler trials between semantically related stimuli does not decrease CSI effects, supporting Prediction Two. See Figure 16 and Table 12 for a summary of the results.

Accuracy Analysis

A Bayesian model that is similar to the models used for analyzing accuracy in Experiment One was used to assess incremental learning effects in Experiment Two. Participant, stimulus, language (*L1*, *L2*) and language of the stimulus (*English*, *Spanish*) were input as random intercepts. Trial type (*stay*, *switch*) and ordinal presentation of a semantically related stimulus (*one* through *six*) were input as fixed effects. There was a main effect of type of trial. Stay trials were 1.88% more accurate than switch trials, and the difference was credible, 95% HDI [0.26, 4.6]. There was also a main effect of ordinal presentation. Naming accuracy decreased by roughly 0.64% with each presentation of a semantic stimulus, 95% HDI [-1.66, -0.09]. There was no credible interaction. The results indicate that naming a semantically related stimulus interferes with naming a semantic neighbor, even after a language switch. See Figure 17 and Table 13 for a summary of the results.

Table 13. *Presentation x Language Accuracy Results based on the Bayesian Model*

Source	Level	Mean	BHM Mean Estimate	Deflection Estimate (%)	95% HDI Lower	95% HDI Upper
Grand Mean		89.7	89.66	*NA*	*NA*	*NA*
Trial Type	Stay	90.5	90.63	0.97*	0.23	2.35
	Switch	88.1	88.69	-0.97*	-2.35	-0.23
Presentation Order	One	92.8	91.10	1.44*	0.19	4.5
	Two	90.6	90.95	1.29*	0.29	3.38
	Three	89.8	89.92	0.26	-0.53	1.63
	Four	88.8	88.99	-0.67	-2.27	0.18
	Five	89.7	89.16	-0.50	-1.9	0.39
	Six	88.4	87.84	-1.82*	-4.81	-0.41
Trial Type x Presentation	Stay One	94.3	92.18	-0.15	-0.94	0.53
	Switch Two	92.2	92.22	0.26	-0.24	1.01
	Stay Three	90.2	90.63	-0.04	-0.64	0.57
	Stay Four	89.9	90.3	-0.08	-0.75	0.5
	Stay Five	89.2	89.42	-0.27	-1.05	0.33
	Stay Six	89.3	89.03	0.27	-0.29	1.15
	Switch One	89.5	90.02	0.15	-0.53	0.94
	Switch Two	87.5	89.68	-0.26	-1.01	0.24
	Switch Three	88.7	89.21	0.04	-0.57	0.64
	Switch Four	86.5	87.68	0.08	-0.5	0.75
	Switch Five	90.5	88.90	0.27	-0.33	1.05
	Switch Six	86.7	86.65	-0.27	-1.15	0.29

*A credible deflection at a 95% HDI was found

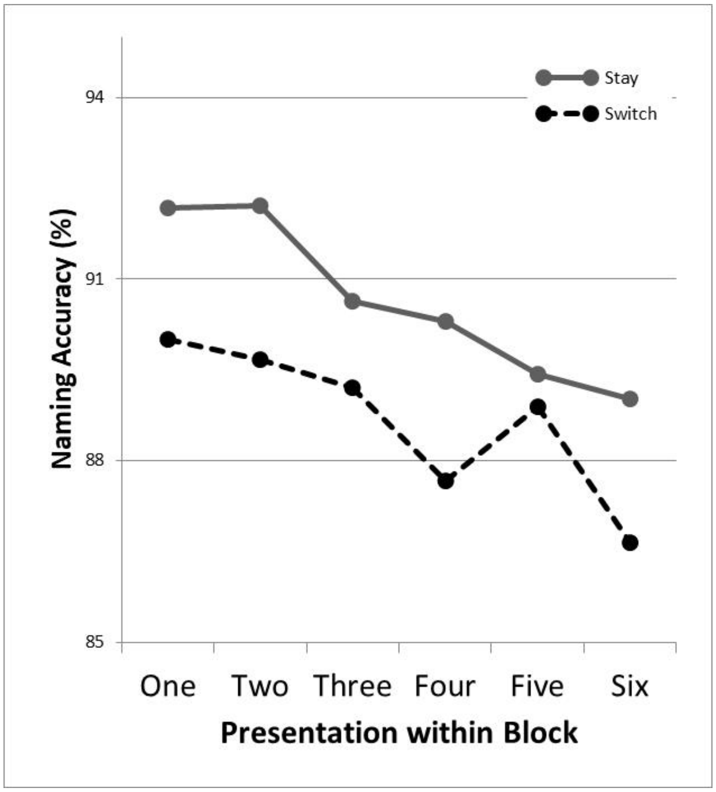


Figure 17. Naming Accuracy by Language and Presentation within Block.

Discussion

In Experiment Two, incremental learning effects were examined. Participants named pictures of semantically related stimuli in a language switching task. Order of type of trial (*stay, switch*) was identical to Experiment One. Unlike Experiment One, the cyclical paradigm was used: Semantically related stimuli were separated by filler trials. If cumulative semantic interference is the result of incremental learning and not spreading activation, then cumulative semantic interference should be unaffected by language switching and the number of intervening filler trials. The data support these hypotheses. With each presentation of a semantic neighbor, naming latency increased on both stay and switch trials by roughly the same amount. Additionally regardless the number of filler trials, with each presentation of a semantic neighbor, naming increased by the same amount. Accuracy also decreased with each presentation of a semantic neighbor. The results of this experiment and trial six of Experiment One indicate that incremental learning creates cumulative semantic interference, and more importantly, incremental learning is largely unaffected by language switching.

Combined with Experiment One, the results of this study help clarify whether inhibition is used to control a bilingual's languages. Using the cyclical paradigm, Runnqvist et al. (2012) found similar results to mine: naming latencies increased with each presentation of a semantic neighbor regardless of whether participants switched languages. They interpreted this as evidence against inhibition as a mechanism of bilingual language control. However, the whole premise of their experiment was that cumulative semantic interference happens because of ever increasing activation among semantic neighbors. Because language switching did not abolish cumulative semantic interference, they concluded that bilinguals do not rely on inhibition. Experiment Two calls that interpretation into question. If cumulative semantic interference is indeed due to ever-increasing activation, then the number of filler trials between presentations of semantic neighbors should affect the rate at which the interference builds. When there are more filler trials, the rate at which naming latency increases should be less than when there are fewer filler trials. This was not the case. In this experiment, the number of filler trials had little effect on cumulative semantic interference. Whether there were fewer than five or five or greater filler trials, naming latency increased at the same rate with each presentation.

In sum, Experiment Two demonstrates that language switching does not abolish cumulative semantic interference. It also provides evidence that cumulative semantic interference is not the result of spreading activation. Rather, it is the result of another mechanism. A likely candidate is incremental learning, as suggested by several researchers (e.g., Damian & Als, 2005; Howard et al., 2006; Navarrete, Del Prato, & Mahon, 2012; Navarrete, Mahon, & Caramazza, 2010).

CHAPTER FIVE:

GENERAL DISCUSSION

This dissertation examined the role of inhibition in bilingual language control. Because the Lexical Selection Mechanism computational model does not assume inhibition is used to control language output, it predicted spreading activation effects would continue after a language switch. Conversely, the Inhibitory Control Model does assume inhibition is used, and it predicted that spreading activation effects would be abolished following a language switch. The results of Experiment One indicate that spreading activation effects were indeed eliminated (as manifested by facilitation on Trials One through Three), supporting the predictions made by the ICM (see Green, 1998a). On trial five of a sub-block (trial four was a switch trial), there was no difference in naming latencies between mixed and uniform stimuli. Experiment Two demonstrated that the cyclical paradigm is not a valid way of testing whether switching languages abolishes residual, spreading activation, and calls into question the methods used in previous research (Hong & MacWhinney, 2011; Lee & Williams, 2001; Runnqvist, Strijkers, Alario, & Costa, 2012). Results indicated that it takes longer to name each additional presentation of a semantically related stimulus, regardless of language switching. This also shows that theories of bilingual language control need to incorporate other mechanisms into their models, specifically incremental learning. Based on the results of these studies, some of the assumptions shared by both the ICM and LSM may need to be reexamined.

The first assumption needing reexamination relates only to the LSM. The LSM proposes that a non-inhibitory mechanism allows bilinguals to control their two languages. The fact that facilitation effects were abolished after a language switch in Experiment One provides evidence against this idea. It is possible that the LSM is correct and that bilinguals use a non-inhibitory mechanism to control language, but one would either have to assume that the results of Experiment One were not reliable, or one could argue that other assumptions researchers make about lexical access are incorrect (e.g., the assumption that words within a language compete and activation flows from the semantic network to both lexicons at a time).

The second assumption that clearly needs reexamination is whether words within a language compete for selection. Based on the remarks of Costa and Caramazza (1999), the LSM assumes that "the degree of activation of non-target nodes affects the ease with which the target word will be selected" (p. 232). Similarly, Green (1998a) when arguing for inhibition in the ICM states, "individuals have difficulty regulating the competition amongst lemmas… via the semantic route" (p. 73). Monolingual models also make this assumption (e.g., Harley, 1993; Levelt, Roelofs, & Meyer, 1999; Roelofs, 1992). Theories assuming that spreading activation creates competition between words predict that RT to words immediately preceded by words in the same semantic category would increase slowly over many trials of related words. These theories predict cumulative semantic interference in a blocked naming paradigm. Such theories might also predict a corresponding increase in naming errors. However, the results of Experiment One indicate that before a language switch, spreading activation from one trial to the next had a credible facilitatory effect over semantically-homogenous trials. Based on the accuracy results, Experiment One (but not Experiment Two) also demonstrated that errors did not credibly increase with each presentation of a semantic neighbor. In fact, the trend in Experiment One was in the opposite direction. These results are consistent with more contemporary research that argues that words (i.e., lexical entries) do not compete for selection (e.g., Navarrete, Del Prato, & Mahon, 2012; Navarrete, Mahon, & Caramazza, 2010; for an explanation as to why models that assume competition may have made the wrong assumptions, see the introduction of Navarrete, Prato, Peressotti, & Mahon, 2014).

The results indicating that words within a language do not compete are somewhat problematic for the ICM. If words within a language do not compete for selection, then why would words between languages compete? And without competition, the case for inhibition in the ICM is greatly weakened, suggesting further that a noninhibitory account like the LSM is more consistent with this finding. However, in Experiment One, the facilitation found in the first three trials of a sub-block was eliminated after a language switch. This suggests that language switching does employ inhibition. Secondly, the ICM proposes that it is not just words that compete. Rather, task schemas compete too. Recall that schemas are defined by the ICM as a mental device or network that people create to complete a given task (Green, 1998a). Theoretically, the competition arises from the two schemas being chosen by the Supervisory Attentional System (i.e., SAS). The ICM can then explain the facilitatory effects in Experiment One by positing that within a schema (i.e., language network) words do not compete; however two active schemas do compete. As both schemas become active, the central executive must choose the correct one, and inhibition may be used to deactivate the non-target schema globally. The ICM model proposes that schemas are deactivated in three ways. Green states that a language schema "remains active until (1) its goal is achieved… (2) it is… inhibited by another schema, or (3) SAS [the Supervisory Attentional System] changes the goal" (p. 69). The fact that facilitation was found in the first three trials is not entirely incompatible with the ICM. However, the results suggest that it is the language networks that create competition for the central executive; within a lexicon, words do not compete with each other.

The third assumption that needs reexamination based on the results of Experiment One is the idea that activation spreads from the semantic network to both lexicons. Getting rid of this assumption, and the assumption that words within a language compete, would allow for a non-inhibitory model of bilingual language control (e.g., the LSM) to work. The basic idea is that activation from the semantic network only flows to one language system at a time. Because there is no competition between words, spreading activation facilitates semantically related trials that occur one after another as long as there is not a language switch (e.g., the first three trials in a sub-block of Experiment One). When there is a language switch (e.g., trial four of the sub-blocks), semantic activation starts flowing to the other language, and any residual activation in the previously activated language decays quickly and naturally without the need for inhibition. There would then be no facilitation when switching back into the original language, because most or all the residual, spreading activation had decayed during the intervening switch trial. This explanation is problematic because it is inconsistent with previous literature that suggests both lexicons receive activation from the semantic network (Colomé, 2001; Hermans, Bongaerts, De Bot, & Schreuder, 1998; Kroll, Bobb, & Wodniecka, 2006). However, further research can test this idea more explicitly.

There is a fourth assumption made by the ICM and LSM that needs reexamining. It is that (in general) activation flows more strongly to a bilingual's first language than to a bilingual's second language. I noticed, based on unpublished research from the lab (Lowry, 2018b), that this might not be the case. When participants had to switch languages on trials with limited inhibitory resources, L1 switch trials were negatively affected more than L2 switch trials were. Recall that inhibition is most needed on L2 switch trials. According to the ICM, limiting inhibitory resources should affect L2 switch trials more than L1 switch trials. The previous lab results, and the results from Experiment One may provide evidence that L2 words receive an extra boost from the semantic network during repeated language switching. Thus, activation may flow more strongly from the semantic network to the L2 lexicon than it does from the semantic network to the L1 lexicon.

Results from Experiment One also provide some support for this. Facilitation on the second trial of a sub-block was greater on L2 trials than on L1 trials. Tentatively, this may suggest that, at least initially during a language switching task, activation flows more strongly to a bilingual's second language than it does to their first. This causes more activation to spread to semantic neighbors in a bilingual's second language and increases the facilitatory effect in L2 compared to the facilitatory effect in L1. Again, such a conclusion is tentative and would need to be corroborated by more research.

The results from this dissertation also show that there is a need for bilingual language control models to incorporate an incremental learning mechanism. In Experiment One, cumulative semantic interference was not abolished after a language switch. In Experiment Two, there was cumulative semantic interference on both stay and switch trials. Its effect did not depend on how many filler trials separated semantic neighbors. The LSM and ICM computational models cannot currently predict this effect without adding additional parameters. In the monolingual domain, there have been calls for the implementation of an incremental learning mechanism into models of lexical access (e.g., Damian & Als, 2005; Howard, Nickels, Coltheart, & Cole-Virtue, 2006). Based on the results of Experiment Two and Runnqvist et al. (2012), it is clear that incremental learning needs to be incorporated into bilingual models of language control as well. More research and modeling are needed to update them.

In conclusion, the results of this dissertation suggest that language switching abolishes spreading activation effects, but cumulative semantic interference (created by incremental learning) is unaffected by language switching. This provides evidence that bilinguals use inhibition in order to control language output, consistent with the ICM. But it also demonstrates the need to update models of monolingual and bilingual lexical access. Specifically, the results indicate that spreading activation does not create competition among lexical entries. They also indicate that models of bilingual language control should incorporate a mechanism of incremental learning. Thus, in answering the question, “How do bilinguals control their language output,” the answer is by using inhibition and by continual (and incremental) adaptation to their environment.

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APPENDIX A:

EXAMINING THE ICM AND LSM COMPUTATIONAL MODELS

The models differ from current models of lexical access in important ways. The first is that the three models try to determine naming latencies at a general level. They do not have nodes for specific words within a lexicon, nor do they have nodes for semantic features. In this way, the models make no assumptions about the decompositionality (or lack thereof) of lexico-semantic connections. This is due to the fact that both the LSM and ICM are relatively silent about how the semantic network connects with a bilingual's two lexicons. The second difference is that the models use a "last target distractor" principle to determine competition-related effects. This means that on any given trial, the last target word is the most salient competitor with the target word. In order for a target to be selected, it must increase its activation so that it is some ratio greater than the last target distractor and other distractors. Many models of lexical access assume that competition depends on the activation levels of all of a target's distractors (e.g., Levelt, Roelofs, & Meyer, 1999; Roelofs, 1992; Roelofs, 1997). However, those models tend to model picture-word interference paradigms rather than blocked naming paradigms trial by trial. Thus, they may not capture the fact that semantic interference may keep increasing as the number of semantically related trials increases. Using the "most active distractor" is a simple way of coding the fact that the previous trial's word interferes with the current trial.

Although not unique to other models, the two models try to explain how naming latencies change trial by trial rather than by blocks of trials. In this way, they can specifically address whether semantic interference/competition resets after language switching.

The ICM Computational Model

This computational model tries to represent lemma activation as proposed by the ICM (Green, 1998a). The original ICM model assumes that top-down control outside of the language system is employed to inhibit the non-target language via task schemas. The top-down control activates language schemas, and those language schemas inhibit lemmas with language tags that do not correspond with the goal of the speaker. The inhibition remains until the speaker's goal is achieved, another language schema inhibits it or the speaker's goal changes. In language switching studies, the goal of the speaker corresponds to the experimental manipulation provided by the researcher (e.g., the participant sees a British flag and knows that the next picture to be named should be in English). The computational model creates goals and mimics how schemas activate and deactivate lemmas during individual trials using two inputs: *language* and *type of trial*. Whether local activation builds up from one trial to the next depends on the inputs *type of trial* and *semantic relatedness*. Because there are 3 inputs (trial type, semantic relatedness, and language) with two levels each (L1/L2, Switch/Stay, True/False), there are 8 possible categories of trials. It should be noted that resting activation (R_l) levels for trial 1 (and non-semantically related trials) are set to the following values at the beginning of the trial:

R_1 (L1 words) = 3.0
R_2 (L2 words) = 1.5

The motivation for setting initial activation levels to non-zero values is twofold. First, it is unlikely that nodes are completely at rest in the lexicon at the start of a block or sub-block. There may be some residual activation from a previous block. The initial activation levels can be changed or estimated for each participant if needed. More importantly, the ICM assumes that inhibition of a language is related to how proficient a bilingual is in that language. By making the resting activation non-zero, inhibition of a language can be modeled by decreasing its activation below its resting activation level.

In the model, the activation of a word ($a_{(j,k,l,m)}$) varies depending on four fixed parameters: type of trial (*j*; stay [*j*=1], switch [*j*=2]), type of word (*k;* target [*k*=*1*], previous target [*k*=2], and other distractors [*k*=*3*]), language (*l*; dominant language [*l*=1], non-dominant language [*l*=2]), and intended language *m* (intended [*m*=1], unintended [*m*=0]). For example, the target word's activation on a stay trial in L1 would be described as $a_{(1,1,1,1)}$ whereas the activation of the target word's translation on a switch trial in the non-dominant language is described as $a_{(2,1,2,0)}$.

It is also assumed that there is a baseline naming latency that is unaffected by semantic relatedness and switching languages (e.g., the time it takes to identify the picture, articulate the sounds etc.). The baseline naming latency is given by the noise parameter (*N*), and is modeled after an ex-Gaussian function. How total reaction time changes depends on whether a trial is a switch or stay. I will first explain stay trials, and then switch trials.

Stay Trials. If a language is active, then it receives activation from the semantic network based on a logistic equation (similar to Oppenheim, Dell, & Schwartz, 2010):

$$(1) \quad s_{j,k,l,m}(t) = \frac{1}{(1 + L_{j,l}e^{-t})}$$

where *L* is a parameter that has an inverse relationship to how fast words in a given language receive activation from the semantic network. Its value depends on the language of the trial, and whether the trial is switch or stay. It is assumed that L1 words have stronger connections to the semantic network. When *j*=1 and *l*=1 (i.e., an L1 stay trial), *L* is small. In contrast, it increases on switch trials because it is assumed that the strong inhibition needed when speaking in L2 on the previous trial must be overcome. In other words, on L1 switch trials, it takes longer for words to activate than on L1 stay trials. L is relatively large when l=2 (i.e., when speaking in the non-dominant language) because it has weaker connections to the semantic network.

t represents how long the lexical network has been receiving information from the semantic network. Its initial value is set to zero. It increases each step by 0.01 "time units" (u) and one of these units is equal to 20ms (i.e., 0.01u= .02ms; u= 20ms). Making u equal to 20ms was done to make the models more computationally efficient. Parameters do not have to be as large, and fewer iterations are needed to get response times that are reasonable. At a given point in time, target words receive some percentage (p) of that activation and distractors split the remaining activation. Thus, $p_{k,m}$ represents the spreading activation parameter from the semantic network to each type of word depending on what the intended language is. If m=1, then the sum of all the target, previous target, other distractors' spreading activation equals one (e.g., $p_{1,1}+p_{2,1}+p_{3,1}=1$). However, p is set to zero for words in the non-intended language (i.e., m=0; e.g., $p_{1,0}=0$, $p_{2,0}=0$, $p_{3,0}=0$). This reflects the idea that the language schemas are controlling activation from the semantic network to the lexical network. For any given trial, the target word in the intended language receives most of the activation (e.g., $p_{1,1}=0.75$) while the distractors in the intended language split the remaining percentage of activation. Thus, activation for a given word is described by the following equation:

$$(2)\quad a_{j,k,l,m}(t) = p_{k,m}s(t)$$

It is also assumed that on stay trials, the non-target language (m=0) is actively being inhibited by the language schemas. How much a word is inhibited is given by the following formula:

$$(3)\qquad I_{j,k,l,m} = ({A_0}_{j,k,l})e^{-\varepsilon_m h_l t}$$

where A_0 is the initial activation of a word at the beginning of the trial. ε determines whether the word is inhibited on a given trial (ε is equal to 0 if the word is in the intended language [m=1], and 1 if it is the unintended language [m=0]). h_l is the inhibition parameter, and its value is depends on the relative strength of a bilingual's language. If a bilingual is strong in both languages, then h_1 and h_2 will be relatively large and equal, indicating that both languages need strong inhibition. If the bilingual is weak in their second language, then h_1 is large while h_2 is small.

In a given stay trial, the total activation of a word at any given point of time ($T_{j,k,l,m}$) can be defined by a word's initial activation plus the sum of all its changes in activation

$$(4)\ \ T_{1,k,l,m} = \left(A_{0j,k,l,m}\right)e^{-(\varepsilon_m h_l t)} + p_{k,m}\left(\frac{1}{(1 + L_{j,l}e^{-t})}\right)$$

An L1 target "wins" once the its activation is some ratio (V) greater than the sum of all other distractor words' activations for both languages:

$$(5)\ \ Target\ Activation \geq\ V(Sum\ of\ All\ Other\ Word\ Activations)$$

$$(6)\ \ T_{1,1,1,1} \geq\ V(T_{1,2,1,1} +\ T_{1,3,1,1} + T_{1,1,2,2} + T_{1,2,2,2} + T_{1,3,2,2})$$

If the target is in the non-dominant language, the equation is similar, except the l subscript changes:

$$(7)\ \ T_{1,1,2,1} \geq\ V(T_{1,2,2,1} +\ T_{1,3,2,1} + T_{1,1,1,2} + T_{1,2,1,2} + T_{1,3,1,2})$$

By replacing the target activation (e.g., $T_{1,1,1,1}$) with T_x and all other non-target words (distractors and translations) with T_d, then V can be represented by the following equation:

$$(8)\ \ \mathrm{V} \leq \left(\frac{T_x}{\sum T_d}\right)$$

Once V is less than or equal to the ratio of the target word and the sum of the distractors, then the target is selected. Until this happens, activation or inhibition is applied to each word. If V=0.55, then one can calculate the time needed by replacing T_x and $\sum T_d$ with their respective equations, and solve for *t*. *t* is then converted to milliseconds and is added to a noise parameter. The noise parameter changes with each trial and is randomly selected from an ex-Gaussian distribution, which has three parameters: mu (μ), sigma (σ) and tau (τ) (see Luce, 1986).

After the word is "selected," the activation decays according to the decay function described above. However, the time that the words decay is determined by the inter-stimulus interval. For the intended language's words, the remaining activation (*A'*) is:

$$(9) \qquad A'_{j,k,l,m} = R_l - [\max(T_{j,k,l,m}(t))]e^{-cy}$$

where *y* is the length of the inter-stimulus interval in time-units, and R_l is the resting activation of language described above. *c* is the decay parameter, and affects how much activation decays between two trials. For the unintended language's words, remaining activation (*A'*) is:

$$(10) \qquad A'_{j,k,l,m} = [\max(T_{j,k,l,m}(t))]e^{-cy}$$

R_l is not added to the final activation to reflect the fact that the unintended language is being actively inhibited.

When trials are semantically related and language doesn't switch, the model assumes that preceding trials have an interfering effect on the current trial due to increased activation within the lexical network. Because of this, initial activation levels are determined by the previous trial. It is assumed that in my experiments, two identical pictures will not be presented more than once in a row during a block, and that pictures will not be repeated within blocks. Because of this, whatever residual activation there was of a target word on trial *n-1* becomes a distractor on trial *n.* Thus, at the beginning of a trial, the last target distractor's activation level is set the final decayed activation level of the target word from the previous trial. Conversely, the target on trial *n* was an "other distractor" on trial *n-1*. Therefore, the initial activation of the target word's activation is set to a value that represents the final activation level of the “other distractors’” activation from the previous trial.

Switch Trials. On switch trials, there is another constraint. All the intended language’s words must reach resting activation levels (R_l). This models the global reactivation of a language when switching back into it. Rectivation (r) of the intended language’s words receives activation according to the following equation:

$$(11) \quad r_{2,k,l,m}(t) = \frac{\varepsilon_m R_l}{(1 + Y_l e^{-t})}$$

where ε determines whether the language gets reactivated. If the word is in the intended language of the trial, it is set to 1. Otherwise, it is set to 0. Also, the rate of reactivation (Y) depends on how strongly the intended language’s words were inhibited (h) and the overall strength of the language (L) on the previous trial, and is proportional to the sum of the language strength parameter on stay trials plus the inhibition parameter (i.e., $Y \propto L_{j=1,l} + h$). The change in reactivation over the change in time during the reactivation period is given by the following equation:

$$(12) \quad \frac{dr_{2,k,l}}{dt} = \varepsilon\left(\frac{R_l Y_l e^t}{(e^t+1)^2}\right)$$

It is assumed that all words from the intended language’s lexicon reactivate at the same rate. The reactivation threshold ($T_{\{0\}_{j,k,l}}$) is given by the following equation:

$$(13) \quad T_{\{0\}2,k,l,m}(t) = \left(A_{\{0\}j,k,l,m}\right)e^{-(\varepsilon_m h_l t_s)} + \varepsilon_m \int_0^{t^*} \frac{R_l Y_l e^t}{(e^t+1)^2}\, dt$$

$$(14) \quad T_{\{0\}2,k,l,m}(t) = \left(A_{\{0\}j,k,l,m}\right)e^{-(\varepsilon_m h_l t_s)} + \varepsilon_m \left[-\frac{R_l Y_l}{e^t+1}\Big|_0^{t^s}\right]$$

The time it takes to reactivate a language is obtained by taking the inverse of the above equation, and the switch cost (δ_{switch}) by converting *t* into milliseconds based on the processing component:

$$(15) \quad t_s = f\left(f^{-1}\left(T_{\{0\}j,k,l}(t_s)\right)\right)$$

$$(16) \quad \delta_{switch} = 20t_s$$

The trial then chooses the target word in the same manner as the stay trials, except time doesn't start at zero for the activation portion of the trial. Rather, it starts at t_s and continues to t:

$$(16) \qquad S(t) = \left(T_{\{0\}2,k,l,m}\right)e^{-(\varepsilon_m h_l t)} + p_{k,m}\left(\frac{1}{(1 + Y_l e^{-(t-t_s)})}\right)$$

Additionally, the rate of activation on switch-trials (measured by the strength parameter *L*) during this period is assumed to be the same as the rate at which the language was reactivated (*Y*). This is based on the idea that on switch trials, inhibition has to be overcome throughout the trial, and not just during the reactivation of the language. Thus, on switch trials, $L_{j=2,l} = Y_l$.

To get a general equation for how activation changes on switch trials, total activation can then be defined as:

$$(17) \quad T_{j,k,l,m}(t) = \begin{cases} T_{\{0\}2,k,l,m}(t), & T_{\{0\}j,k,l,1}(t) < R_l \\ S(t), & T_{\{0\}j,k,l,1}(t) > R_l \end{cases}$$

In order for the target to be selected, it must meet the same requirements found in Equation 8: *V* must be less than or equal to the ratio of the target activation divided by the distractors. The time interval can then be determined by taking the inverse of *V*. At the end of the trial, activation decays in the same way as in stay trials (see Equations 9 and 10).

Assessing a word's activation and the model's parameters. In order to assess the model's activation, the activations of the words were plotted by time for an L1 stay trial for 10 time units without having a target “win” (see Figure A1). Additionally, activation was plotted over time for two trials an L1 stay and L2 switch) based on how the model chooses a winner (see Figure A2).

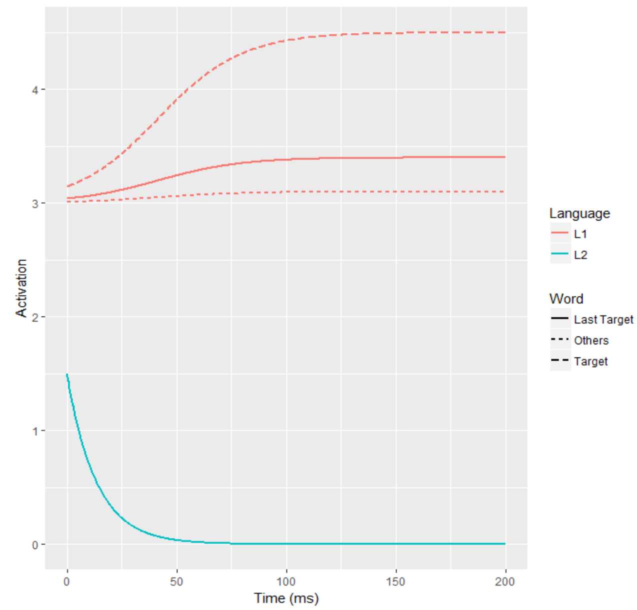

Figure A1. How activation of each type of word (e.g., Target, Last Target, etc.) changes over time for each language (L1, L2) for a single L1stay trial of the ICM

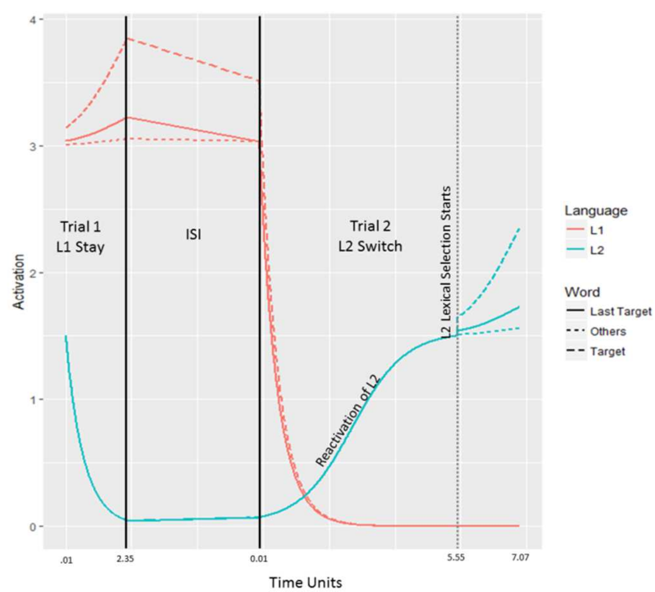

Figure A2. How activation of each type of word (e.g., Target, Last Target, etc.) changes over time for each language (L1, L2) for two trials of the ICM (L1 stay, L2 switch)

As can be seen from Figure A1, as words in L1 become active, L2 words are inhibited. In Figure A2, two trials are shown: an L1 stay and then an L2 switch. In this figure, the targets win according to Equation 8. On trial two (an L2 switch trial), any activation in L1 is immediately inhibited. All words (i.e., distractors and the target) in L2 are reactivated at the same rate at the beginning of the trial. Once they have been reactivated, the L2 target starts receiving input from the semantic network and the distractors receive some portion of that activation according to Equation 16.

In the ICM computational model, there are 10 free parameters: three parameters for spreading activation, $p_{k,m=1}$ (one for each type of word k in the intended language), two inhibition parameters (h_l), two language strength parameters ($L_{j,l}$), two resting activation parameters (R_l), the value (V) that represents the ratio of the target's activation in the intended language over all other activations, the rate of decay parameter c, and the reactivation parameter Y. Most can be set a priori, or be allowed to vary randomly. $p_{k,m=1}$ is based on the percentage of activation that one thinks the target word receives. Once that is determined, the distractors split the remaining activation. The language strength parameters on stay trials ($L_{j=1,l}$) and resting activation parameters (R_l), can be set based on a bilingual's rating of their balance (e.g., the more unbalanced a bilingual is, the greater L_2 will be compared to L_1; the more unbalanced a bilingual is, the greater R_l will be compared to R_2). On switch trials, $L_{j=2,l} = Y_l$. Y_l is proportional to the inhibition parameter (h_l) and language strength parameter $L_{j=1,l}$. It can simply be set to a value of 1, or any other number. V must be set to a value that is greater than $min\left(\frac{T_m}{\sum T_d}\right)$, and less than $max\left(\frac{T_m}{\sum T_d}\right)$. If $V < min\left(\frac{T_m}{\sum T_d}\right)$, then there can be no semantic interference from one trial to the next because V multiplied by the target activation (i.e., $V \times T_x$), it will always be greater than the sum of the distractor activations$(\sum T_d)$. However, if $V > max\left(\frac{T_m}{\sum T_d}\right)$, then a target will never be chosen. Thus, the closer V is to the minimum value, the less semantic interference there is from one trial to the next; the closer V is to the maximum value, the more semantic interference there is from one trial to the next. Similarly, the rate of decay parameter c must be set to a value that allows for there to be residual activation from one trial to the next. If c is too large, all activation will decay during the inter-stimulus interval. Below, I consider how changing parameters affects reaction times for a block of six trials that are all semantically related.

For demonstration purposes, unless otherwise stated, I set the parameters to the following values: L_1=1.5 and L_2=5 (this assumes that L_1 is the dominant language); $p_{k=1,m=1}$ = 0.75 (the other distractors split the remaining activation evenly); R_1=3.0 and R_2=1.5; c=0.01; $p_{1,1}$=0.75 and h_1= h_2=3.0. Because Y depends on L and h, its value is not fixed. However, in the simulations, it was set to roughly five times the sum of L and h. These values give results consistent to what one might expect a priori based on the literature. A set of six semantically related trials were simulated (L1 stay, L1 stay, L1 stay, L2 switch, L1 switch, L1 stay).

Varying the decay parameter c. In the Figure A3, I vary the decay parameter c, keeping all other parameters constant. c is set to 0.005, 0.01, or 0.05. If c is too small (i.e., 0.005), there is not enough decay, allowing too much activation to build from one trial to the next. Competition becomes increasingly problematic (e.g., see trial three when c is set to 0.005 in Figure A3). If c is too large (i.e., 0.05), interference from one trial to the next are abolished because most residual activation has decayed from the previous trial. I choose to use 0.01 as the value of c because it allows for just the right amount of residual activation to remain from trial n to trial $n+1$, which increases naming latencies by about 20-30ms each trial.

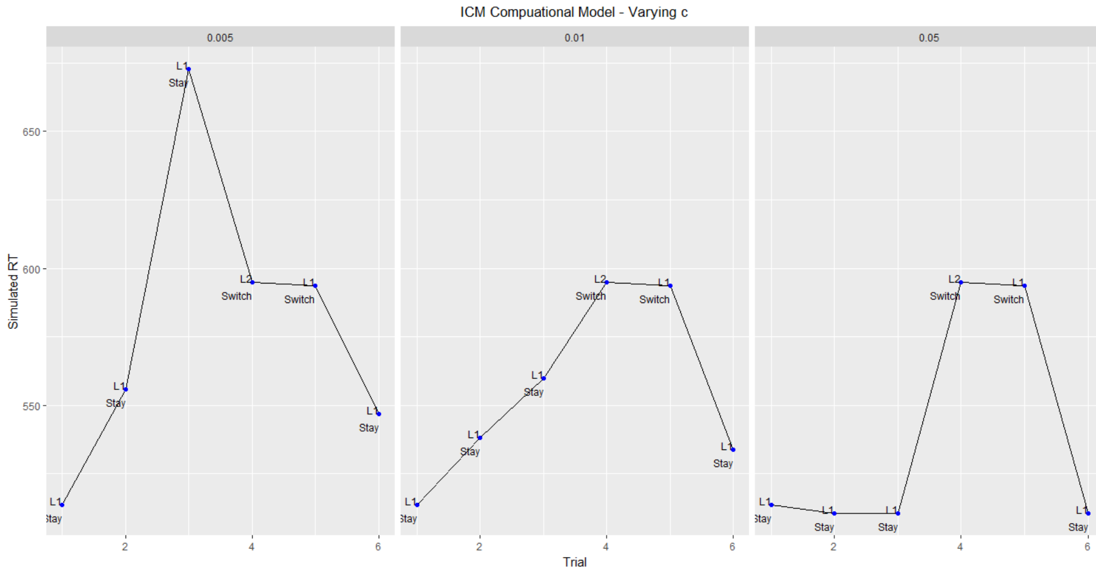

Figure A3. How varying *c*, the decay parameter, affects naming latencies for the ICM computational model.

Varying the L1 language strength parameter for stay trials. In Figure A4, it shows how I vary the L1 language strength parameter on stay trials ($L_{j=1,1}$), keeping all other parameters constant. The model was simulated three times, setting $L_{j=1,1}$ to 0.2, 1.5 and 5. Changing the L1 strength parameter mostly affects how fast a target word is chosen (i.e., compare trial one in each of the three panels in Figure 5). The lower the value, the faster the words become active and meet the conditions needed for the target to "win" (see equation 12). Additionally, if the strength parameter is too small, it can offset the competition that occurs due to residual activation from one trial to the next (see the first three trials in the first panel [i.e., $L_{j,1} = 0.2$] of Figure 5). The L1 strength parameter also affects the L1 switch costs, since Y_l is partially dependent on it.

Figure A4. How varying $L_{j,1}$, the L1 strength parameter, affects naming latencies for the ICM computational model.

Varying the target's spreading activation parameter p_k. In Figure A5, it shows how I vary the spreading activation coefficient parameter p for the target word. p behaves similarly to c, but for different reasons. If p is too small for the target word, too much activation gets spread to its semantic competitors. It becomes increasingly difficult for the conditions to be met described in Equation 12 (i.e., it becomes difficult for the ratio of target activation to its distractors to reach V). Competition quickly becomes a problem (see left panel of Figure A5). Conversely, if p is too large for the target word, there is very little competition due to the conditions described in equation 12 being met almost immediately at the beginning of the trial (see the right panel in Figure 6). 0.75 is therefore a reasonable value for the target's spreading activation coefficient that ensures competition, while keeping it in check at the same time. Once p for the target has been determined, p coefficients for the other distractors become fixed (i.e., the sum of all p's must equal one and the distractors split the remaining activation). It should be noted that varying *V* changes reaction times in a similar way as varying *p*, although in the opposite direction. If *V* is too small, the conditions in Equation 12 are met almost instantaneously, resulting in no competition. If it is too big, it becomes increasing difficult to meet equation 12's requirements, resulting in ever-increasing naming latencies.

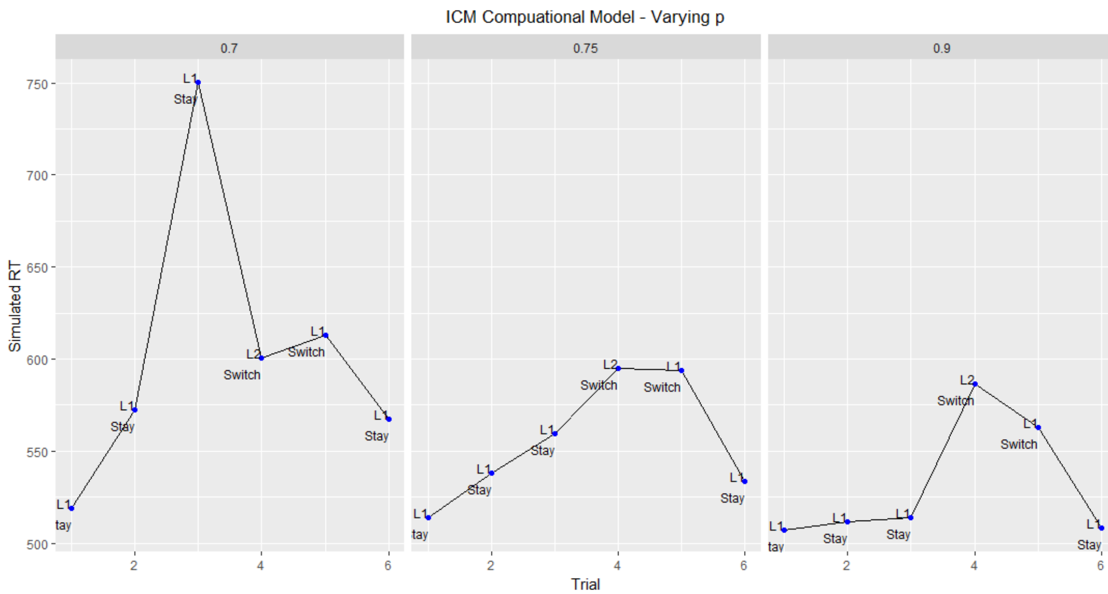

Figure A5. How varying the spreading activation coefficient parameter *p* for the target word affects naming latencies for the ICM computational model.

Varying the reactivation parameter Y. In Figure A6, it shows how I vary the reactivation parameter *Y.* As can be seen by comparing the three panels, *Y* controls the switch costs. If its value is large, then the target language on a switch trial takes more time to reach residual activation. If it is too small, there is little switch cost. A value of 5.0-6.0 gives reasonable switch costs.

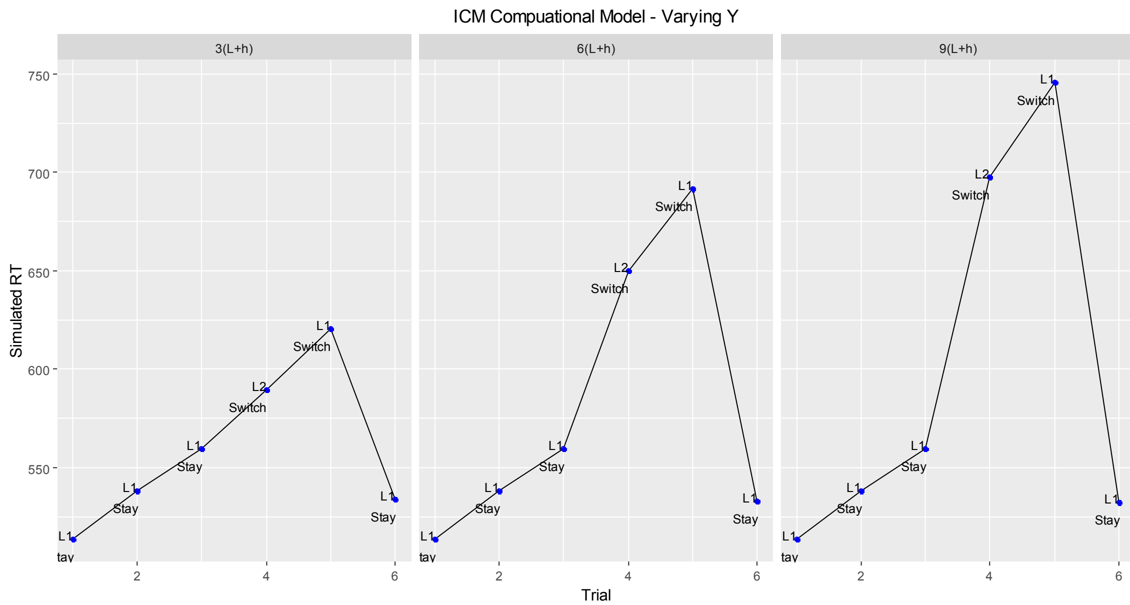

Figure A6. How varying the reactivation parameter *Y* for affects naming latencies for the ICM computational model.

Varying the inhibition parameter, h. In Figure A7, it shows how I varied the inhibition parameter *h*. Like *Y*, *h* has a large effect on the switch costs. The larger *h* is, the larger the switch cost. This is somewhat counterintuitive. However, the ICM states that the cost of switching back into a language will be proportional to how much that language was inhibited previously. This is consistent with the way the computational model behaves. However, Figure A7 also demonstrates the benefit of *h* being relatively large: between language competition is mitigated on the first trial (i.e., naming latencies are faster on trial one when *h*=5 than when *h*=1). On trial one, both languages are active. The more inhibition there is of L2, the faster a target can be chosen in L1 on trial one.

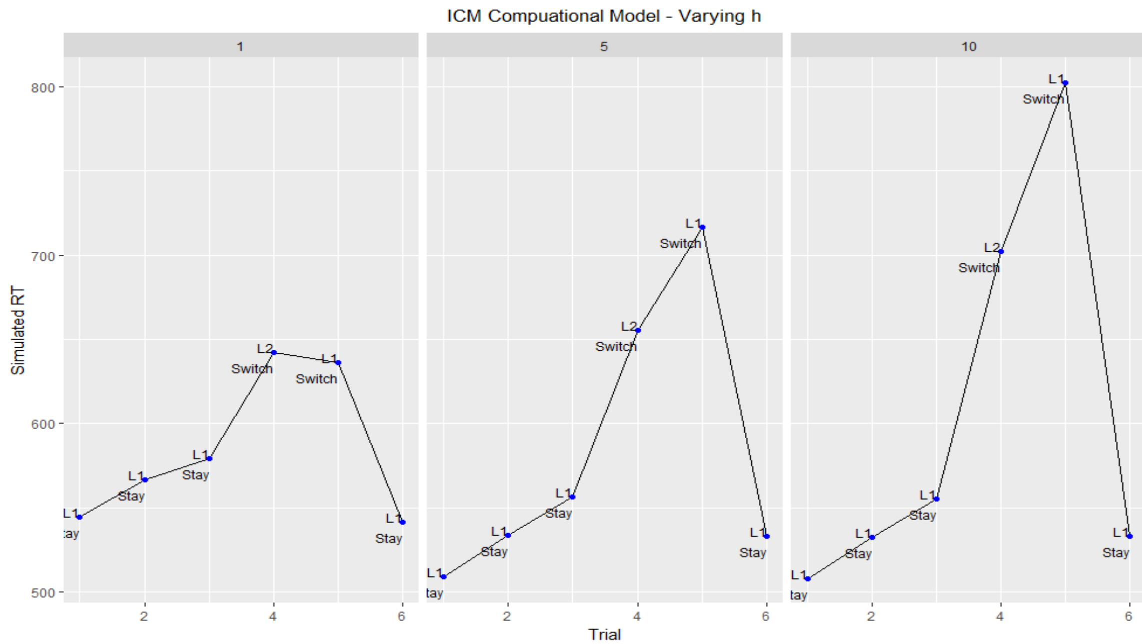

Figure A7. How varying the inhibition parameter *h* affects naming latencies for the ICM computational model.

Final thoughts on parameter manipulation. In summary, most parameters can be reasonably chosen a priori. Specifically, all of the *L, p, Y* and *c* parameters can be treated as fixed parameters in order to make sure the model is not underspecified. *h* can then be estimated based on the data from the experiments.

It should also be noted that no matter how the parameters change, trial six in the simulations always had a similar naming latency to trial two. This relationship holds up even when simulating a block of mixed trials (i.e., semantic category changes on trial four). The model assumes that on switch trials, all words in the unintended language are inhibited. Because of this, there is no parameter that can be changed that will make trial six be affected by semantic interference from the first three trials. In other words, whether a block is mixed or uniform in the experiment, trial six is unaffected.

The LSM Computational Model

The LSM computational model is similar in all respects to the ICM model with two major exceptions. The first is that during switch trials, no inhibition occurs of the target language. Both switch and stay trials can be described by the following equations:

$$(18) \qquad T_{j,k,l} = A_{0(j,k,l)} + p_{k,l}\frac{1}{(1 + L_{j,l}e^{-t})}$$

$p_{k,l}$ is now greater than zero for the unintended language's words, allowing activation to spread to both lexicons on a trial. Like the ICM, the targets (e,g., the target in L1 and its translation in L2) receive most of the activation. Distractors in both languages split the remaining activation, meaning both languages are affected by spreading activation from the semantic network. Note that there is no inhibition applied to any of the words.

Additionally, the LSM assumes that only words within a language compete. Instead of the target activation needing to be some ratio larger than all the distractors (i.e., within and between language), it only needs to be some ratio larger than the distractors in its language (i.e., the intended language). For a stay trial in L1, this would be represented by the following equations:

$$(19)\ Target\ Activation \geq V(Sum\ of\ Distractor\ Activations)$$

$$(12)\ T_{1,1,1,1} \geq V(T_{1,2,1,1} + T_{1,3,1,1})$$

t can be found using similar calculations in the ICM computational model.

Also notice that there is no longer the constraint of reactivating the intended language's words on a switch trial because inhibition did not take place on the previous trial. After the word is "selected," the activation decays for all words similarly to how activation decays for the intended language in the ICM model:

$$(20) \qquad A'_{j,k,l} = [\max(T_{j,k,l}(t))]e^{-cy} + R_l$$

Assessing activation and the model's parameters. In order to assess the model's activation over one trial, the activations of the words were plotted over time without having the target "win" (see Figure A8). Additionally, activation was plotted over two trials (see Figure A9). Unlike the ICM, there is no inhibition of the non-target language. Most of the activation flows to the target and its translation, with spreading activation affecting distractors in each language.

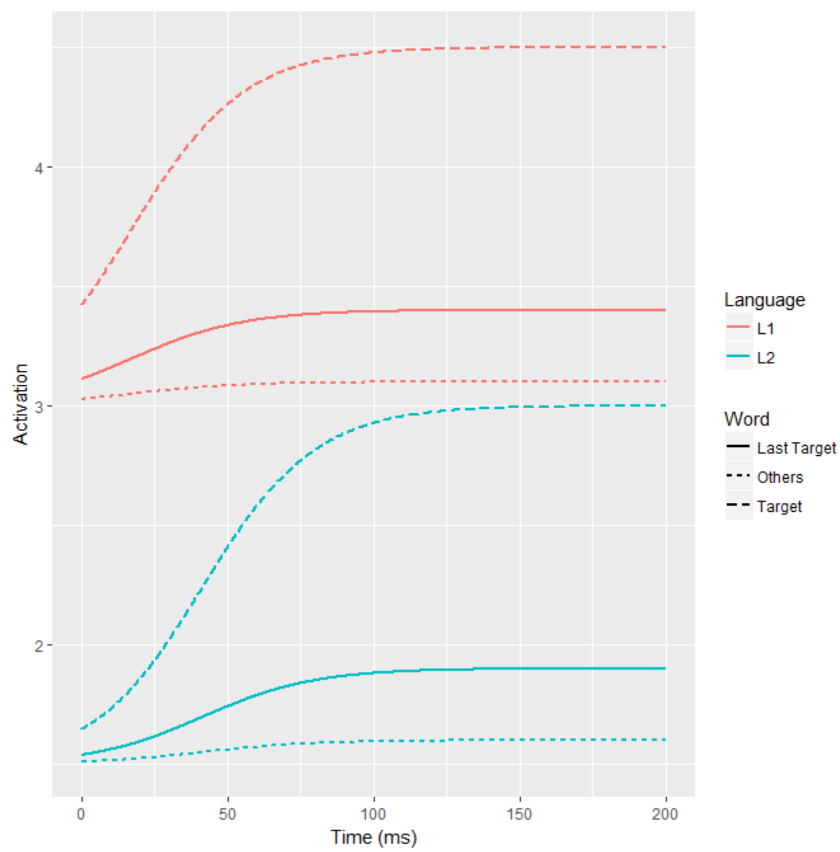

Figure A8. How activation of each type of word (e.g., Target, Last Target, etc.) changes over time for each language (L1, L2) for one trial of the LSM

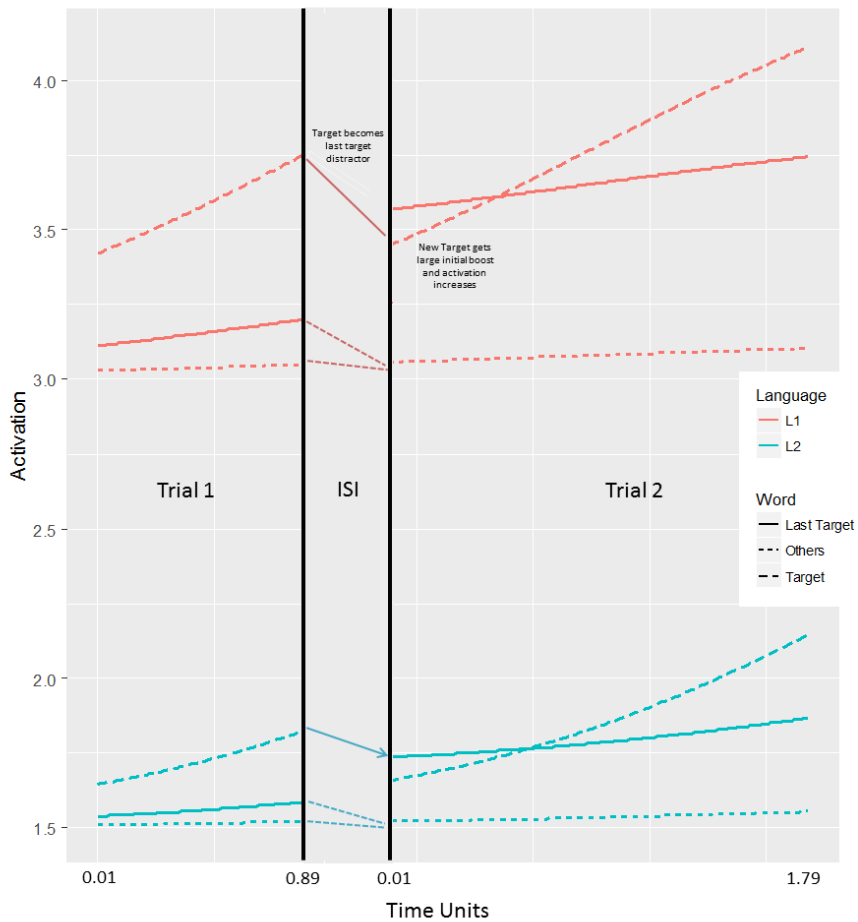

Figure A9. How Activation changes over time for each type of word (e.g., Target) for both languages over two L1 Stay Trials. Arrows in the interstimulus interval (ISI) demonstrate that the target word's activation decays and becomes the initial activation of the "Last Word" distractor on the next trial.

There are the same parameters in the LSM model as in the ICM model except for *Y* and *h,* which don't exist in this model. These are replaced by language strength parameters. The parameters behave similarly, except semantic interference from the first three trials can affect trial six because no inhibition occurred when switching languages. Thus, most of the parameters can be fixed a prior, similar to the ICM if needed. However, because *h* does not exist, the model will estimate the language strength parameters (*L*) on switch trials between the two languages. This is analogous to examining *h* because *L* on switch trials determines the switch cost. .

APPENDIX B:

SUBJECTIVE LANGUAGE QUESTIONNAIRE

Q. Age: What is your age? ________________________________

Q. Gender

- ○ Female
- ○ Male

Q. What is your primary language?

- ○ English
- ○ Spanish
- ○ Other

Q. What is your secondary language?

- ○ English
- ○ Spanish
- ○ Other

Q. At what age did you begin to learn your secondary language? ____________________

Q. Proficiency in *speaking* in primary language 1 2 3 4 5 6 7

(1=not proficient, 7=native/highly proficient).

Q. Proficiency in *writing* in primary language 1 2 3 4 5 6 7

(1=not proficient, 7=native/highly proficient).

Q. Proficiency in *reading* in primary language 1 2 3 4 5 6 7

(1=not proficient, 7=native/highly proficient).

Q. Proficiency in *speaking* in secondary language 1 2 3 4 5 6 7

(1=not proficient, 7=native/highly proficient).

Q. Proficiency in *writing* in secondary language 1 2 3 4 5 6 7

(1=not proficient, 7=native/highly proficient).

Q. Proficiency in *reading* in secondary language 1 2 3 4 5 6 7

(1=not proficient, 7=native/highly proficient).

APPENDIX C:

STIMULI USED IN EXPERIMENTS ONE AND TWO AND THEIR RELEVANT PROPERTIES

Stimuli were assessed in terms of their prototypicality, familiarity, frequency and number of syllables. Spanish words do not differ from English words in terms of the first three variables. However, Spanish words tend to have more syllables on average than English words. From a theoretical perspective, a difference in the number of syllables should not matter as much as a difference between prototypicality and familiarity since number of syllables a word has is related to phonological planning and not lemma retrieval. The important variable to control is whether the Spanish words come from the same semantic category (since spreading activation within the semantic network flows to lemmas), which is reflected in the prototypicality ratings. Association norms were also analyzed in order to make sure that stimuli within and across categories did not have an association link. Additionally, the picture stimuli were normed by 10 native English-Spanish bilinguals. Each participant named the stimuli once in each language without prompts to ensure that the names corresponded to the pictures. Then, they named the pictures 10 times each in each language in random order to become familiar with the stimuli. Table A1 gives means, standard deviations and 95% HDI intervals based on Bayesian t-tests for the variables of interest in Spanish and English. Mean reaction times and accuracy for each word are based on data from the 10 bilingual speakers. Prototypicality and familiarity ratings were taken from Schwanenflugel & Rey (1986). Word frequencies were taken from the Corpus of Contemporary

American English and Corpus del Espano (Davies, 2017a; Davies, 2017b). Additionally, norms for each individual word are found in Table A2.

Table A1. Average Word Properties by Language

	Group	N	Mean	SD	SE	95% Credible Interval	
						Lower	**Upper**
Reaction Times (ms)	English	48	1254	127.1	18.34	1218	1290
	Spanish	48	1247	163.5	23.60	1201	1293
Accuracy (%)	English	48	91.9	6.3	0.9	90.1	93.7
	Spanish	48	88.3	9.5	1.4	85.6	91.0
Protypicality	English	48	5.730	0.917	0.132	5.470	5.991
	Spanish	48	5.313	0.971	0.140	5.037	5.589
Familiarity	English	48	6.386	0.802	0.116	6.158	6.614
	Spanish	48	6.487	0.594	0.086	6.318	6.655
Per Million Freq	English	48	33.661	45.844	6.617	20.635	46.686
	Spanish	48	17.876	47.170	6.808	4.474	31.279
Syllables*	English	48	1.850	0.828	0.093	1.668	2.032
	Spanish	48	2.688	0.793	0.198	2.294	3.081

*Note: there is a credible difference between English and Spanish words in terms of syllables.

Table A2. Stimuli and Associated Word Properties Used in Experiments One and Two.

Picture Stimulus	English						Spanish					
	Word	Proto	Fam	Freq	RT	Acc.	Word	Proto	Fam	Freq	RT	Acc.
	airplane	6.45	6.96	14.23	1195	95	avion	4.94	6.96	35.73	1025	97
	apple	6.82	6.92	37.48	1209	97	manzana	6.52	7	14.44	1131	98
	arm	6.64	7	92.72	1258	94	brazo	6.66	6.88	25.12	1181	96
	arrow	4.46	3.65	9.4	1137	98	flecha	6.16	6.36	5.69	1196	94

	bass	5.14	5.44	20.87	1478	90	bajo	4.68	5.21	322.86	1206	83
	bed	6.46	6.92	132.9	1053	98	cama	6.12	6.52	45.78	1034	97
	bench	3.7	6.56	24.82	1177	90	banco	3.48	6.6	10.49	1176	88
	bookshelf	4.34	6.64	1.72	1449	86	estante	3.78	6.2	1.21	1389	87
	bugle	5.53	5.36	0.78	1414	77	clarin	4.42	4.04	9.05	1629	63

	car	6.58	6.82	265	1200	94	automovil	6.88	6.96	14	1205	87
	chair	6.74	6.92	83.11	1118	96	silla	5.78	7	19.59	1115	97
	chicken	4.8	6.8	52.53	1265	97	gallina	3.76	6.92	3.24	1161	94
	cymbal	4.42	5.88	0.24	1458	86	platillo	3.6	6.21	3.23	1531	79
	desk	6.28	6.88	54.93	1239	96	escritorio	5.46	6.84	17.6	1326	88

	dress	6.76	6.8	61.08	1111	99	vestido	6.38	6.8	30.43	1115	94
	drum	6.18	6.76	10.75	1242	97	tambor	5.12	6.54	3.64	1387	92
	duck	5.24	6.8	11.82	1145	97	pato	3.54	6.84	1.61	1234	93
	eagle	6.52	6.6	13.98	1176	95	aguila	5.84	6.32	6.17	1225	88
	elbow	5.28	6.8	13.43	1329	90	codo	5.53	6.68	5.3	1397	86

	grapefruit	6.2	6.56	2.51	1509	91	toronja	5.4	6.84	0.68	1304	74
	gun	6.76	6.84	92.6	1243	90	pistola	6.1	5.24	4.01	1218	95
	harp	5.66	6.2	2.5	1317	93	arpa	5.8	5.54	1.71	1091	92
	pocket-knife	3.69	4.1	0.24	1275	84	navaja	5.68	6.4	2.55	1418	82
	knee	5.62	6.8	30.28	1161	99	rodilla	5.62	6.68	10.41	1173	95

	knife	6.1	3.69	35.87	1116	99	cuchillo	6.96	5.52	8.48	1211	93
	mouth	6.78	7	47.28	1056	95	boca	6.4	6.84	13.37	972	99
	nose	5.6	6.88	50.61	1036	96	nariz	5.76	6.76	16.93	891	99
	orange	6.76	7	48.11	1200	99	naranja	6.36	7	16.4	1221	97
	parakeet	6.08	6.68	2.7	1246	78	perico	5.63	6.88	0.44	1280	88

	peach	6.3	6.32	6.33	1468	87	melocoton	5.56	6.72	0.89	1603	75
	plum	5.72	5.8	4.99	1467	81	ciruela	4.9	6.64	0.63	1580	70
	seagull	6.34	6.48	0.67	1297	90	gaviota	5.4	6.4	1.58	1557	62
	ship	5.28	6.52	61.98	1286	76	barco	4.76	6.84	24.83	1236	89
	shirt	6.94	6.88	44.45	1309	96	camisa	6.28	7	12.08	1135	97

	shoe	5.24	6.64	16.71	1053	97	zapato	4.8	6.92	5.07	1016	99
	shotgun	6.42	6.88	10.23	1324	85	escopeta	5.4	6.16	2.5	1315	85
	shoulder	5.92	6.76	67.81	1443	89	hombro	5.8	6.68	12.47	1342	86
	skirt	6.68	6.68	16.21	1177	93	falda	5.72	6.48	5.84	1150	94
	speedboat	3.86	6.32	0.56	1326	85	lancha	3.26	6.64	2.6	1281	83

	strawberry	6.04	6.68	1.55	1163	95	fresa	5.44	6.64	2.56	1049	98
	streetcar	4.68	5.44	10.07	1418	82	tranvia	4.84	6.04	1.98	1454	68
	suit	5.86	6.72	9.09	1266	98	traje	5.48	6.92	18.74	1202	92
	swan	5.04	6.36	10.69	1201	96	cisne	4.73	6.32	2.12	1288	81
	sword	5.72	5.88	15.21	1131	97	espada	4	6.4	15.63	1301	82

	table	6.72	6.96	0.66	1310	87	mesa	6.58	7	81.48	1170	97
	tie	4	6.44	3.17	1110	97	corbata	3.88	6.72	4.41	1193	92
	truck	5.56	6.84	61.72	1225	96	camion	5.6	6.84	10.67	1230	92
	xylophone	5.14	5.68	59.12	1390	87	marimba	4.24	5.42	1.83	1311	81

APPENDIX D:

IRB APPROVAL LETTER AND CONSENT FORM

USF UNIVERSITY OF SOUTH FLORIDA

RESEARCH INTEGRITY AND COMPLIANCE
Institutional Review Boards, FWA No. 00001669
12901 Bruce B. Downs Blvd., MDC035 • Tampa, FL 33612-4799
(813) 974-5638 • FAX (813) 974-7091

September 5, 2017

Mark Lowry, B.A.
Psychology
4202 East Fowler Ave.
Tampa, FL 33620

RE: **Expedited Approval for Initial Review**
IRB#: Pro00032200
Title: Testing Theories of Bilingual Language Control

Study Approval Period: 9/4/2017 to 9/4/2018

Dear Mr. Lowry:

On 9/4/2017, the Institutional Review Board (IRB) reviewed and **APPROVED** the above application and all documents contained within, including those outlined below.

Approved Item(s):
Protocol Document(s):
Theories of Bilingual Langauge Control Version 1 1-18-2017.docx

Consent/Assent Document(s)*:
SB Adult Minimal Risk Theories os Bilingual Language Control.docx.pdf

*Please use only the official IRB stamped informed consent/assent document(s) found under the "Attachments" tab. Please note, these consent/assent documents are valid until the consent document is amended and approved.

It was the determination of the IRB that your study qualified for expedited review which includes activities that (1) present no more than minimal risk to human subjects, and (2) involve only procedures listed in one or more of the categories outlined below. The IRB may review research through the expedited review procedure authorized by 45CFR46.110. The research proposed in this study is categorized under the following expedited review category

(6) Collection of data from voice, video, digital, or image recordings made for research purposes.

(7) Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies.

As the principal investigator of this study, it is your responsibility to conduct this study in accordance with IRB policies and procedures and as approved by the IRB. Any changes to the approved research must be submitted to the IRB for review and approval via an amendment. Additionally, all unanticipated problems must be reported to the USF IRB within five (5) calendar days.

We appreciate your dedication to the ethical conduct of human subject research at the University of South Florida and your continued commitment to human research protections. If you have any questions regarding this matter, please call 813-974-5638.

Sincerely,

John A Schinka, Ph.D.

John Schinka, Ph.D., Chairperson
USF Institutional Review Board

Informed Consent to Participate in Research Involving Minimal Risk

Pro # 00032200

You are being asked to take part in a research study. Research studies include only people who choose to take part. This document is called an informed consent form. Please read this information carefully and take your time making your decision. Ask the researcher or study staff to discuss this consent form with you, please ask him/her to explain any words or information you do not clearly understand. The nature of the study, risks, inconveniences, discomforts, and other important information about the study are listed below.

We are asking you to take part in a research study called:

Testing Theories of Bilingual Language Control

The person who is in charge of this research study is Mark Lowry. This person is called the Principal Investigator. However, other research staff may be involved and can act on behalf of the person in charge. He is being guided in this research by Dr. Chad Dube and Dr. Liz Schotter.

The research will be conducted at the University of South Florida.

Purpose of the study

The purpose of this study is to try to understand how bilingual speakers are able to produce words in their first and second languages.

Why are you being asked to take part?

We are asking you to take part in this research study because you have indicated that you are bilingual.

Study Procedures:

If you take part in this study, you will be asked to:

- *Take part in naming pictures in either your first or second language.*
- *You will also be asked to fill out a brief questionnaire about how well you know your first and second languages.*
- *In total, the entire procedure will not take more than 1 hour 15 minutes.*
- *It will take place in PCD 3109.*
- *In order to accurately measure how long it takes you to start naming each picture, audio will be recorded for each trial. The audio recording will not be given to anyone except the*

researcher and the research team. The recording will be kept secure on an encrypted drive. It will not be linked to any identifiable information. It will be kept for 5 years after the final report is submitted to the USF IRB. After which, it will be deleted.

Total Number of Participants

About 150 individuals will take part in this study at USF.

Alternatives / Voluntary Participation / Withdrawal

You do not have to participate in this research study.

You should only take part in this study if you want to volunteer. You should not feel that there is any pressure to take part in the study. You are free to participate in this research or withdraw at any time. There will be no penalty or loss of benefits you are entitled to receive if you stop taking part in this study.

Benefits

You will receive no benefit(s) by participating in this research study.

Risks or Discomfort

This research is considered to be minimal risk. That means that the risks associated with this study are the same as what you face every day. There are no known additional risks to those who take part in this study.

Compensation

If you signed up through SONA, you will be compensated 3 SONA point. If you withdraw for any reason from the study before completion you will be compensated 1 SONA point.

You will receive no payment or other compensation for taking part in this study.

Costs

It will not cost you anything to take part in the study.

Privacy and Confidentiality

We will keep your study records private and confidential. Certain people may need to see your study records. Anyone who looks at your records must keep them confidential. These individuals include:

- The research team, including the Principal Investigator and all other research staff.
- Certain government and university people who need to know more about the study, and individuals who provide oversight to ensure that we are doing the study in the right way.
- Any agency of the federal, state, or local government that regulates this research.
- The USF Institutional Review Board (IRB) and related staff who have oversight responsibilities for this study, including staff in USF Research Integrity and Compliance.

We may publish what we learn from this study. If we do, we will not include your name. We will not publish anything that would let people know who you are.

You can get the answers to your questions, concerns, or complaints

If you have any questions, concerns or complaints about this study, or experience an unanticipated problem, call Mark Lowry at XXX-XXX-XXXX.

If you have questions about your rights as a participant in this study, or have complaints, concerns or issues you want to discuss with someone outside the research, call the USF IRB at (813) 974-5638 or contact by email at RSCH-IRB@usf.edu.

Consent to Take Part in this Research Study

I freely give my consent to take part in this study. I understand that by signing this form I am agreeing to take part in research. I have received a copy of this form to take with me.

_______________________________________ _____________
Signature of Person Taking Part in Study Date

____
Printed Name of Person Taking Part in Study

Statement of Person Obtaining Informed Consent

I have carefully explained to the person taking part in the study what he or she can expect from their participation. I confirm that this research subject speaks the language that was used to explain this research and is receiving an informed consent form in their primary language. This research subject has provided legally effective informed consent.

_______________________________________ _____________
Signature of Person obtaining Informed Consent Date

____
Printed Name of Person Obtaining Informed Consent