

## Scaling Single-Program Performance on Large-Scale Chip Multiprocessors

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### Abstract

*Due to power constraints, computer architects will exploit TLP instead of ILP for future performance gains. Today, 4–8 state-of-the-art cores or 10s of smaller cores can fit on a single die. For the foreseeable future, the number of cores will likely double with each successive processor generation. Hence, CMPs with 100s of cores—so-called large-scale chip multiprocessors (LCMPs)—will become a reality after only 2 or 3 generations.*

*Unfortunately, simply scaling the number of on-chip cores alone will not guarantee improved performance. In addition, effectively utilizing all of the cores is also necessary. Perhaps the greatest threat to processor utilization will be the overhead incurred waiting on the memory system, especially as on-chip concurrency scales to 100s of threads. In particular, remote cache bank access and off-chip bandwidth contention are likely to be the most significant obstacles to scaling memory performance.*

*This paper conducts an in-depth study of CMP scalability for parallel programs. We assume a tiled CMP in which tiles contain a simple core along with a private L1 cache and a local slice of a shared L2 cache. Our study considers scaling from 1–256 cores and 4–128MB of total L2 cache, and addresses several issues related to the impact of scaling on off-chip bandwidth and on-chip*

communication. In particular, we find off-chip bandwidth increases linearly with core count, but the rate of increase reduces dramatically once enough L2 cache is provided to capture inter-thread sharing. Our results also show for the range 1–256 cores, there should be ample on-chip bandwidth to support the communication requirements of our benchmarks. Finally, we find that applications become off-chip limited when their L2 cache miss rates exceed some minimum threshold. Moreover, we expect off-chip overheads to dominate on-chip overheads for memory intensive programs and LCMPs with aggressive cores.

## 1 Introduction

Due to power budget constraints, computer architects now scale the number of cores on a chip, relying on thread-level parallelism (TLP) instead of instruction-level parallelism (ILP) for future performance improvements. This requires sufficient TLP exists in the first place to effectively utilize the available cores. Not surprisingly, workloads exhibiting TLP “out of the box”—*e.g.*, multiprogrammed and transaction processing workloads—have been the primary sources of TLP to date. But as programmers and compilers become more proficient at exposing TLP in sequential codes, parallel programs will increase in importance. This will enable *single-program performance*, in addition to system throughput, to benefit from chip multiprocessor (CMP) scaling.

The performance benefits from program parallelization are potentially significant due to the large number of cores that will become available in future CMPs. Today, 4–8 state-of-the-art cores or 10s of smaller cores [1, 2] can fit on a single die. Since Moore’s law scaling is expected to continue at historic rates for the foreseeable future [3], the number of cores will likely double with each successive processor generation. CMPs with 100s of cores—so-called large-scale CMPs (LCMPs) [4, 5]—will become a reality after only 2 or 3 generations. While not all programs will be able to exploit LCMPs, many applications in emerging domains, such as data mining [6], bioinformatics [7], and machine learning [8], exhibit abundant TLP. For these applications, LCMPs offer the potential for

unprecedented performance gains.

Unfortunately, simply scaling the number of on-chip cores alone will not guarantee improved performance for parallel programs. In addition, effectively utilizing all of the cores is also necessary. Perhaps the greatest threat to achieving high processor utilization will be the overhead incurred waiting on the memory system, especially as concurrency reaches 100s of threads. Hence, the *scalability of the memory hierarchy* will be critical to realizing performance on LCMPs.

Two sources of memory overhead are most likely to limit scalability. One of them is *remote cache access*. To keep up with the enormous volume of memory requests generated by 100s of cores, the on-chip cache in an LCMP will be aggressively banked and distributed across the die. Banking gives rise to non-uniform cache access due to each core's varying proximity to the different cache banks [9], resulting in higher latency and greater on-chip communication traffic. Data replication and migration techniques [10, 11, 12] can help bring a core's working set into nearby banks, but their effectiveness can be limited. As core count and cache capacity scale, the volume of and distance to remotely situated data will likely increase, exacerbating the remote cache access problem.

Another scaling limitation is *contention for off-chip bandwidth*. As more and more cores are integrated, the number of simultaneous requests to off-chip memory will increase. However, due to packaging constraints, off-chip bandwidth is expected to grow much more slowly than core count [13], potentially creating a bottleneck at the off-chip interface. Even for uniprocessors [14] and small-scale CMPs [15], the off-chip bandwidth bottleneck can already be severe. The problem will become worse for LCMPs.

Understanding the limits on CMP scaling for parallel programs, particularly due to remote cache access and contention for off-chip bandwidth, is crucial to the design of future LCMPs. Despite its importance, surprisingly little is known about this problem. While there have been numerous studies to mitigate remote cache accesses [16, 17, 18, 19, 20, 12, 21, 22], none of them have considered

CMPs with more than 16 cores. Hence, there is no experience with remote cache access at the LCMP scale. In comparison, more is known about off-chip bandwidth contention. Several researchers have studied contention effects at 100s of threads [23, 4, 15, 13, 5]. However, these studies focused on throughput workloads only, providing no insight for parallel programs. Moreover, none of them considered last-level caches with more than 32MB—large by today’s standards, but potentially small for future LCMPs.

This paper improves the state-of-the-art understanding of LCMPs by conducting an in-depth study on their scalability for parallel programs. Our study assumes a tiled CMP [11] in which tiles contain a simple core along with a private L1 cache, a local slice of a shared L2 cache, and a switch for a 2-D on-chip mesh network. We develop a simulator that employs a very simple core model, but accurately simulates the memory hierarchy to enable detailed evaluation of its scaling. Using this simulator, we evaluate LCMPs with up to 256 cores/tiles and 128MB of total L2 cache.

Our work addresses three major questions. First, how does off-chip bandwidth vary with thread and cache capacity scaling? We characterize the variation in off-chip bandwidth across the complete cross product of CMPs containing 1-256 cores and 4-128MB of L2 cache. We find off-chip bandwidth varies significantly across different applications, suggesting the right amount of off-chip bandwidth that future LCMPs should provide is highly application dependent. Our results also show off-chip bandwidth often increases linearly with core count; however, for parallel programs with data sharing, the rate of bandwidth increase reduces dramatically once enough L2 cache is provided to capture inter-thread data sharing.

Second, how does on-chip communication vary with thread scaling? We examine the fraction of L2 references destined to remote tiles for the same CMP design space mentioned above. For our shared L2 cache, we find the total on-chip communication scales as  $P^{\frac{3}{2}}$ , where  $P$  is the number of cores. We also find for the range 1–256 cores, there is ample on-chip bandwidth to support

the communication requirements for all our benchmarks. And lastly, what is the relative impact of the off-chip and on-chip memory overheads on overall scalability? We conduct performance simulations to quantify the contribution of both sources of memory overhead to IPC. Our results show when the L2 miss rate is larger (smaller) than a *break-even miss rate*, the off-chip (on-chip) overhead dominates. For our benchmarks, both off-chip and on-chip overheads are significant, with the former being slightly more dominant. Given larger problem sizes and more aggressive cores, we expect the off-chip bottleneck will become even more dominant.

The remainder of this paper is organized as follows. Section 2 discusses related work. Then, Section 3 presents our experimental methodology. Next, Sections 4 and 5 study scaling’s impact on off-chip bandwidth and on-chip communication, respectively, and Section 6 shows their relative impact on overall performance. Finally, Section 7 concludes the paper.

## 2 Related Work

Several researchers have conducted CMP design space explorations [23, 4, 15, 24, 25, 13, 5]. Our work is closely related to these previous studies. Like them, we vary core count and on-chip cache capacity, quantifying the impact these parameters have on off-chip bandwidth and overall performance. But to our knowledge, we are the first to investigate CMPs with up to 256 cores and 128MB last-level caches (LLCs). Early studies considered much smaller CMPs—up to 32 cores and 32MB LLCs [24, 25]. Other studies considered larger CMPs in terms of cores—up to 128 [4, 15]—but still assumed fairly small LLCs—up to 32MB. Still other studies considered CMTs with up to 34 cores [23, 5], but studied large-scale parallelism—up to 240 threads—when factoring in per-core multithreading. But these studies also employed relatively small LLCs—up to 18MB.

Compared to previous research, our work looks much farther down the scaling roadmap, particularly in the amount of on-chip cache (32MB LLCs are soon-to-be, if not already, realizable). Perhaps more importantly, previous work only sampled a limited number of CMP configurations,

whereas our study explores the complete cross product of 1-256 cores and 4-128MB LLCs, shedding light on the entire design space. One recent study does look at a design space comparable to ours [13], but they report analytical results only. In contrast, our study provides simulation results.

Another key difference is previous studies focused primarily on throughput workloads—in particular, multiprogrammed [15, 24, 13] and transaction processing workloads [23, 4, 5]. Instead, we consider parallel programs, so our results reflect the impact of LCMPs on single-program performance. As such, sharing plays a greater role in our work. (While transaction processing does exhibit sharing, previous studies [4, 5] employed trace-driven simulation that assumed 0% sharing between per-thread traces). In terms of workloads, our study is closest to [25] which also investigated parallel programs. But as mentioned earlier, this study only considers 32 cores.

Our work is also closely related to research on LLC organization and the related techniques to improve on-chip physical locality. Large LLCs are typically banked, where the banks are managed as *shared* or *private* with respect to cores. Shared caches permit flexible use of the aggregate cache capacity, resulting in low miss rate, whereas private caches keep each core’s data physically close, resulting in low access time. Significant research has tried to combine shared and private schemes to inherit benefits from both. Some techniques start from a shared organization, but permit migration [10, 17, 19] or replication [11] to bring cache blocks closer to their referencing core(s). Other techniques start from a private organization, but allow some sharing by pushing victims into neighboring banks exhibiting less capacity pressure [16, 26, 27]. Because these techniques are performed at the cache block level, they require changes to the cache lookup and/or coherence protocol hardware. To mitigate hardware complexity, there has also been significant research on page-based techniques [28, 18, 12, 20]. These techniques start from a shared organization, but perform intelligent placement, migration, and replication of pages in the OS to improve physical locality.

Similar to this prior research, our work also addresses cache utilization and physical locality issues for banked LLCs. But rather than develop new techniques, we focus on *characterizing* the utilization and locality issues when scaling to 100s of cores. We study the scheme with the smallest hardware requirement (and also the best cache utilization)—a basic shared cache without migration or replication—as this approach has the greatest chance for scaling to 100s of cores. Our goal is to quantify how severe the on-chip physical locality problem becomes for this simple approach, especially in comparison to off-chip overheads. To our knowledge, our work is the first to consider physical locality issues for 256 cores—previous research on LLC locality management has not considered more than 16 cores—and to examine the relative importance of on-chip versus off-chip memory overheads at this large scale.

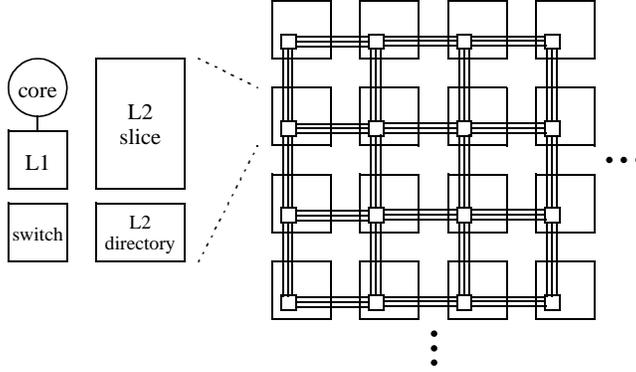
Finally, our work investigates performance scaling only; we do not consider how power scales. A small number of previous CMP studies have looked at power scaling [24, 25], but the majority have not. Understanding the limitations on scaling LCMPs due to power constraints is critical, and an important direction for future work.

### 3 Experimental Methodology

This section presents our experimental methodology. Section 3.1 discusses architectural assumptions. Then, Section 3.2 presents our simulator, and Section 3.3 describes our benchmarks.

#### 3.1 Tiled CMPs

All experiments performed in this paper assume a tiled CMP architecture, illustrated in Figure 1. In a tiled CMP, multiprocessor hardware resources are grouped into tiles, which are replicated given the available chip area to form the overall CMP. In particular, the tile (or replication unit) includes a processing core, a private L1 cache, an L2 cache “slice” and cache coherence directory, as well as a switch with associated point-to-point interconnect for a 2-dimensional mesh on-chip network. As tiles are replicated, *all* CMP resources—including cores, cache, and communication—increase



**Figure 1. A tiled CMP architecture consists of replicated tiles, with each tile containing a processing core, a private L1 cache, an L2 cache “slice” and directory, and a switch with associated point-to-point interconnect.**

proportionally. For this reason, the tiled CMP is regarded as a scalable CMP organization [18, 11], and hence, a good candidate for our study.

A crucial component of the tiled CMP is the L2 slice. All of the L2 slices form a single shared L2 cache, which serves as the chip’s LLC. As such, the aggregate miss rate across the L2 slices determines the off-chip bandwidth consumption. In addition, data placement in the L2 slices also determines on-chip communication. If cores primarily reference data in L2 slices on the same or nearby tiles, very little inter-tile communication will occur; otherwise, significant communication can occur. Due to their impact on off-chip bandwidth and on-chip communication, the L2 slices are a major focus of this paper.

Our study assumes the L2 slices are managed as a simple shared cache, with no migration or replication across L2 slices. Instead, each cache block resides in a single fixed L2 slice—also known as the cache block’s “home”—during its entire lifetime in the L2 cache. Moreover, we assume cache blocks are block-interleaved across L2 slices according to their physical address, with blocking factor equal to 1-way of an L2 slice (512B or larger, depending on the cache configuration). As discussed in Section 2, this shared cache organization ensures effective utilization of the aggregate L2 cache capacity since per-thread working sets are distributed evenly across tiles. In addition, due to its

simplicity, it is easy to scale in terms of hardware complexity. However, it does not attempt to colocate cores with their referenced data, exacerbating remote cache accesses.

To help address remote cache accesses, we manage the L1 caches as private caches, permitting replication of data in each core’s local L1. Coherence across L1 caches is maintained via directory-based cache coherence using a MESI protocol. We assume each cache block’s directory entry is colocated with its associated data, *i.e.* on the cache block’s home tile. Moreover, we assume full-map directories, with each slice of the directory containing an entry for every cache block in its associated L2 slice. This approach can lead to large directories. However, much lower directory overhead can be achieved by maintaining the directory as a cache since the number of active directory entries grows with the total chip-wide L1 capacity and not the L2 capacity. We do not evaluate such an optimization in this paper.

### 3.2 Simulator

For our experiments, we use the M5 simulator [29], modified to model the tiled CMP described in Section 3.1. Specifically, we implemented a directory-based cache coherence protocol, and added a 2-dimensional point-to-point mesh network. In addition to the changes for tiled CMPs, we also significantly modified M5’s memory sub-system model to support multiple DRAM channels (4 in our case), each associated with a memory controller placed on a special “memory tile” at the periphery of the on-chip mesh network. In our simulator, we place the memory controllers on the north and south faces of the chip, evenly spaced part. In total, we model 32 GB/sec off-chip bandwidth.

Table 1 details the simulator configurations used in our experiments. As the table shows, we assume a very simple processor model that (in the absence of memory stalls) executes a single instruction per cycle, regardless of the instruction’s type, in program order. This simplification is needed to enable the large simulations in our study. However, we model all aspects of the memory

Number of Tiles	1 – 256
Core Type	Single issue, In-order, CPI = 1, clock speed = 2GHz
IL1/DL1	32KB/32KB, 64B block, 4-way, 1 cycle
Total L2 Cache Size	4MB – 128MB, L2 Slice: 64B blocks, 32-way, 10 cycles
2D Mesh	3 cycles per-hop, bi-directional channels, 256-bit wide links
Memory channels	latency: 300-CPU cycles, bandwidth: 4x8B/cycle with bus speed = 1GHz

**Table 1. Simulator parameters used in the experiments.**

hierarchy accurately. In particular, we account for all latencies, including L1 access, hops through the on-chip network, L2 slice access, and DRAM access. The latter includes latency for the first word and transfer of remaining words. In addition to these latencies, we also account for queuing delays at the on-chip network switches as well as the memory controllers during DRAM accesses.

In Sections 4 and 5, we consider a large design space, consisting of the cross product of tiled CMPs with 1–256 cores and 4–128MB of total L2 cache. When scaling the L2 cache, we always assume the total capacity is evenly divided amongst tiles; hence, the size of each L2 slice is always the total L2 size divided by the number of tiles. These experiments only consider total traffic, either to off-chip memory or across the on-chip network, and thus do not account for latency. In Section 6, we conduct simulations that additionally account for latency to quantify the impact of the on-chip/off-chip traffic on performance. All of our experiments only consider execution of application code without any operating system code (*i.e.*, the OS is emulated) due to the difficulty of performing full-system simulations at 256 cores.

In addition to the above simulator modifications, we also created a basic user-level threading library that provides support for thread creation/termination and lock/barrier synchronization. The synchronization primitives are implemented on top of shared memory, with all the associated shared memory overheads accurately simulated.

Benchmark	Problem Size	Insts(Billions)	Simulation Region
MADD	4,096 x 2,048	0.101	whole program
FFT	$2^{22}$ elements	2.61	whole program
LU	4,096 x 4,096	26.90	first 8 iterations
KMeans	1,238,650 Objects, 16 features	9.31	1 timestep
BlackScholes	3,145,728 options	4.52	1 timestep
Barnes	524,288 particles	55.22	1 timestep

**Table 2. Parallel benchmarks used to drive the simulations.**

### 3.3 Benchmarks

Table 2 lists the benchmarks used in our study. We employ 6 parallel programs in total: matrix add (MADD), FFT, LU decomposition, KMeans, BlackScholes, and Barnes-Hut. FFT, LU, and Barnes are from the SPLASH2 suite [30], while KMeans is from the NU-MineBench suite [6] and BlackScholes is from the PARSEC suite [31]. MADD is our own implementation of matrix add.

The second column of Table 2 indicates the problem size used for each benchmark. In all our simulations, we execute the initialization portion of each program on a single core. (For all of our benchmarks, initialization is performed sequentially). After simulation of the initialization code, we clear statistics, and simulate the parallel region for the number of instructions reported in the third column of Table 2. For MADD and FFT, the parallel regions we simulate represent the entire program. For KMeans, BlackScholes, and Barnes, we simulate 1 timestep of the algorithm. This is indicated in the last column of Table 2. For all of our results, we report the statistics only from the parallel region.

## 4 Scaling Impact on Off-Chip Bandwidth

We begin our study by investigating off-chip bandwidth requirements. Section 4.1 introduces our bandwidth metric, P-way bytes/instruction (PBI), and uses it to quantify off-chip bandwidth. Then, Section 4.2 introduces our analysis on constant-PBI contours. Lastly, Section 4.3 continues this analysis, accounting for what we call “small-slope regions” in our CMP design space.

	MADD	FFT	LU	KMeans	BlackScholes	Barnes
8C/4MB	16.01	1.85	0.32	0.16	0.15	0.090
32C/16MB	63.20 (3.9)	7.52 (4.1)	1.22 (3.8)	0.65 (4.1)	0.53 (3.5)	0.33 (3.7)
128C/64MB	236.47 (3.7)	27.38 (3.6)	4.36 (3.6)	2.53 (3.9)	1.77 (3.3)	0.75 (2.3)
256C/128MB	354.73 (1.5)	33.40 (1.2)	1.84 (0.42)	1.41 (0.56)	1.71 (0.97)	0.20 (0.27)
256C/64MB	477.39	56.68	7.87	4.96	3.51	1.45
256C/32MB	501.27	63.48	8.03	5.21	4.18	2.38

**Table 3. L2-PBI given constant grain size scaling (first 4 rows), and for varying grain size at 256 cores (last 2 rows). Values in parentheses indicate L2-PBI increase for each step in core count.**

#### 4.1 Post-L2 P-Way Bytes-per-Instruction

Off-chip bandwidth is determined by several factors, including number of cores, core and memory architecture, clock rate, and application characteristics. Later in Section 6, we will account for all these factors. Here, we study the off-chip bandwidth arising from interactions between the application and the memory hierarchy, disregarding the core architecture and clock rate impact. For sequential programs, an appropriate metric for this purpose is bytes/instruction. To extend this metric for CMPs, we multiply the average bytes/instruction by the number of cores,  $P$ . We call this metric *P-way bytes/instruction*, or PBI. PBI is appropriate for parallel programs that exploit loop-level parallelism (like ours) since the threads execute the same code, and hence, tend to exhibit similar bytes/instruction. In addition, since actual bandwidth = PBI  $\times$  per-core IPC  $\times$  clock rate, PBI provides an intuitive feel for the bandwidths one could expect to see on a real machine. (For example, PBI=1 implies 2GB/sec bandwidth if we assume an ideal per-core IPC=1 and clock rate = 2GHz).

In this section, we characterize off-chip bandwidth by quantifying PBI for the post-L2 cache-miss stream. We call this the L2-PBI. Table 3 reports L2-PBI across our parallel programs for several CMP configurations. The first 4 rows of Table 3 show L2-PBI for 8, 32, 128, and 256 cores. At each core count, the L2 slice size is kept constant at 512KB—*i.e.*, the 4 configurations have constant *grain size* (cache per core). As Table 3 shows, L2-PBI varies dramatically across applications. FFT and MADD exhibit very large L2-PBI, reaching 33.40 and 354.73 at 256 cores; BlackScholes,

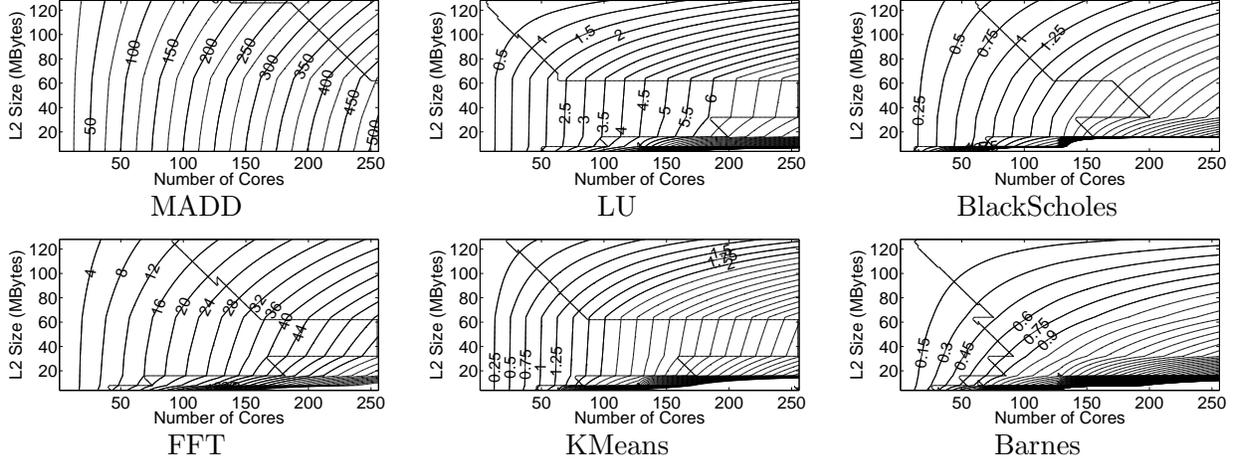
KMeans, and LU exhibit much smaller—but still significant—L2-PBI, reaching 1.77, 2.53, and 4.36, respectively, at 128 cores; and Barnes has very small L2-PBI, reaching only 0.75 at 128 cores. This high L2-PBI variation demonstrates our application suite has very diverse locality characteristics, and suggests the amount of off-chip bandwidth necessary for LCMPs in the future will be highly application dependent.

Table 3 also shows L2-PBI increases with core count in most cases, but not uniformly. When scaling from 8 to 32 cores—a 4x increase—the applications exhibit a roughly 4x L2-PBI increase as well (except for BlackScholes). However, when scaling from 32 to 128 cores—the next 4x increase—the applications exhibit a noticeably smaller 2.3–3.7x L2-PBI increase (except for KMeans). And for the last 2x scaling from 128 to 256 cores, FFT and MADD’s L2-PBI increase by only 1.2x and 1.5x, respectively, while the L2-PBI for LU, KMeans, BlackScholes, and Barnes actually *decrease*. This non-linear L2-PBI growth has significant implications for CMP scalability, and will be explained later in Section 4.2.

The last 2 rows in Table 3 report L2-PBI for 256-core machines as the L2 slice size is varied from 512KB down to 256KB and 128KB (thus also reducing total L2 cache). Not surprisingly, L2-PBI increases significantly as cache is reduced, especially when going from 512KB to 128KB L2 slices. This highlights the importance of the LLC in mitigating off-chip bandwidth.

## 4.2 Constant L2-PBI Contours

Section 4.1 shows L2-PBI generally increases with core scaling and decreases with cache capacity scaling; this was demonstrated for a few CMP configurations. In this section, we study a much larger CMP design space to extract more insight on core-vs-capacity scaling. For each application, we simulate the complete cross product of 1–256 cores and 4–128MB of L2 cache, stepping by powers of 2 along each scaling dimension, and measure the L2-PBI each time. By interpolating between the simulated values, we obtain an “L2-PBI surface” across our entire CMP design space.



**Figure 2. Contours of constant L2-PBI in our CMP design space for the 6 parallel applications.**

We then trace contours of constant L2-PBI, creating a 2-dimensional “relief map” on top of the L2-PBI surface.

Figure 2 presents the constant L2-PBI contour graphs for our applications. In each graph, core and L2 capacity scaling are plotted along the X- and Y-axes, respectively. Labels indicate the L2-PBI values for several contours in each graph. Figure 2 shows L2-PBI generally increases from the upper left to the lower right corner of our CMP design space. This makes sense since L2-PBI usually increases with core scaling and decreases with capacity scaling. While the actual L2-PBI values vary, except for extreme cases, they roughly correspond to the value ranges reported in Table 3 (FFT and MADD exhibit large L2-PBI; LU, KMeans, and BlackScholes exhibit moderate L2-PBI; and Barnes exhibits small L2-PBI).

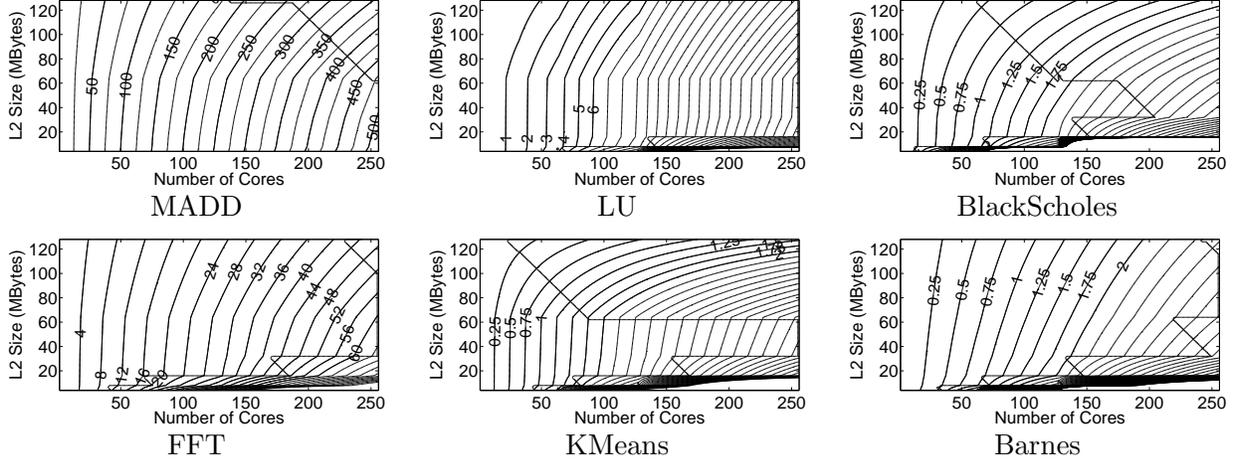
Figure 2 highlights the relative impact of core and cache capacity scaling on L2-PBI. In particular, the *slope* along any constant L2-PBI contour reflects the cache capacity scaling rate needed to maintain the corresponding L2-PBI value given some core scaling rate. Slope = 1 signifies cache should be scaled at the same rate as cores to maintain constant L2-PBI, while slope  $>$  ( $<$ ) 1 signifies cache should be scaled at a faster (slower) rate as cores to maintain constant L2-PBI. To emphasize this slope information in Figure 2, lines have been drawn to cut across the constant L2-PBI contours where slope = 1, thus partitioning our CMP design space into “large-slope” ( $>$

1) and “small-slope” ( $< 1$ ) regions.

In general, one would expect constant L2-PBI contours to exhibit large slope due to the added cache pressure that core scaling induces. As mentioned earlier, our parallel programs exploit loop-level parallelism, so threads execute the same code and tend to have similarly sized working sets. If per-thread working sets are mostly non-overlapping, the aggregate chip-wide working set size will grow proportionally as core count increases. To maintain constant miss rate (and bytes/instruction), cache capacity must usually grow faster than increase in working set size (one common assumption is quadratic growth [13]). To maintain constant *P-way* bytes/instruction, cache capacity must grow *even faster*.

Indeed, a significant portion of each constant L2-PBI contour in Figure 2 resides in a large-slope region. Below some core count, the large-slope regions span the majority of cache sizes. This occurs at around 50 cores for all applications except MADD; for MADD, it occurs closer to 200 cores. Beyond this point, the large-slope regions span cache sizes up to about 64MB. (Barnes, and to some extent BlackScholes, do not exhibit this second large-slope region). CMPs in these large-slope regions exhibit *inefficient scaling* since any additional chip area would need to be apportioned mostly for cache rather than for cores to avoid off-chip bandwidth bottlenecks.

Interestingly, contrary to the expected behavior, a large portion of our CMP design space also lies within small-slope regions. As Figure 2 shows, the constant L2-PBI contours “flatten” towards the upper right corner, creating a significant small-slope region in most benchmarks. With the exception of MADD which doesn’t have much of a small-slope region, our benchmarks exhibit small-slope regions above roughly 64MB of L2 cache and beyond about 50 cores. The small-slope regions in Barnes and BlackScholes are even larger, spanning all cache sizes at larger core counts. CMPs in these small-slope regions exhibit *efficient scaling* since any additional chip area could be apportioned mostly for cores rather than for cache without incurring significantly higher off-chip



**Figure 3. Contours of constant L2-PBI in our CMP design space adjusted to exclude data sharing.**

bandwidth. Hence, they are desirable parts of the CMP design space from a scalability standpoint.

### 4.3 Accounting for Small-Slope Regions

Small-slope regions occur when scaling core count does not appreciably increase capacity pressure on the L2 cache. One reason this might happen is *sharing*. Separate threads from the same parallel program often share data. If this sharing is captured in the L2 cache, then increasing the number of cores will not significantly grow the chip-wide working set, thus permitting slower cache capacity scaling.

To quantify this effect, we modified our simulator to compute the L2-PBI that would have occurred had threads not been allowed to share data in the L2 cache. Specifically, the modified simulator tracks which cores reference each L2 cache block since the block was brought into cache. This allows the simulator to identify L2 hits that are a core’s first touch of the cache block (*i.e.*, the hit occurs because another core incurred an earlier cache miss on the shared block). The simulator counts an additional L2 miss (and appropriately increases the L2-PBI) for such first-touch hits since they would have been cache misses in the absence of sharing. (Note, the extra L2 misses are not actually simulated, so they do not introduce replication in the shared L2 cache).

Figure 3 presents the constant L2-PBI contour graphs assuming L2-PBI values that have been

adjusted to exclude sharing. In Figure 3, we see the small-slope regions for LU, FFT, and Barnes in Figure 2 have almost completely disappeared, leaving behind a single large-slope region that essentially fills the entire CMP design space. This result shows sharing is primarily responsible for the small-slope regions in Figure 2 for these 3 benchmarks. An important observation is that sharing’s impact on L2-PBI does not occur when the cache is too small. For smaller caches, cache block lifetimes in the L2 are not sufficiently long to capture inter-thread sharing references. In our experiments, the minimum capacity needed to realize L2 data sharing is roughly 64MB.

For the remaining benchmarks—MADD, BlackScholes, and KMeans—there isn’t a significant difference between Figures 2 and 3; hence, sharing is not prevalent in these benchmarks, and cannot explain their small-slope regions. As mentioned earlier, MADD doesn’t have a significant small-slope region. It is extremely memory intensive; its L2-PBI essentially grows linearly with core count, and is not noticeably reduced by cache scaling. The cause for small-slope regions in BlackScholes and KMeans is low miss rates. For these benchmarks, significant portions of the benchmarks’ entire working set fits in 128MB of cache. As these problems are parallelized across more cores, the additional threads do not place much more pressure on the cache (even though there isn’t much sharing), so small increments in cache size can maintain a constant L2-PBI.

Finally, for most benchmarks, a thin small-slope region exists at the bottom of the constant L2-PBI contour graphs. Due to the small cache sizes in this portion of the design space, cache thrashing occurs beyond about 50 cores. Because essentially everything misses in the cache, the miss rate and L2-PBI are relatively constant as more cores are added. This represents pathologic behavior, and is not an interesting part of the CMP design space.

## 5 Scaling Impact on On-Chip Communication

Next, we continue our study by investigating on-chip communication requirements. In particular, on-chip communication bandwidth depends on two factors: the traffic out of the private L1

	MADD	FFT	LU	KMeans	BlackScholes	Barnes
8C/4MB	32.09	7.29	1.29	0.33	4.47	4.43
32C/16MB	116.85 (3.6)	29.18 (4.1)	5.34 (4.1)	1.33 (4.0)	18.00 (4.0)	18.33 (4.1)
128C/64MB	509.36 (4.4)	116.45 (4.0)	23.23 (4.4)	9.17 (6.9)	72.02 (4.0)	76.12 (4.2)
256C/128MB	1012.67 (2.0)	232.51 (2.0)	49.95 (2.2)	18.54 (2.0)	144.00 (2.0)	146.77 (1.9)
256C/64MB	1013.01	232.58	50.09	18.61	144.14	148.23
256C/32MB	960.04	232.29	50.41	18.72	145.32	148.02

**Table 4. L1-PBI given constant grain size scaling (first 4 rows), and for varying grain size at 256 cores (last 2 rows). Values in parentheses indicate PBI increase for each step in core count.**

caches, and the distance each L1-to-L2 request travels across the on-chip network. The next section studies these two factors. Armed with this understanding, Section 5.2 then investigate how on-chip bandwidth scales.

### 5.1 L1-PBI and Physical Locality

To quantify the traffic out of the private L1 caches, we use the same PBI metric from Section 4.1. However, here we measure the PBI of the post-L1 (instead of post-L2) cache-miss stream. We call this the L1-PBI. Table 4 reports L1-PBI across our parallel programs for the same CMP configurations (and in the same format) as Table 3. As Table 4 shows, L1-PBI is considerably larger than L2-PBI. For example, for CMPs with 256 cores and 128MB L2 cache, MADD’s L1-PBI is 2.9 times larger than its L2-PBI; FFT, LU, and KMeans’ L1-PBI are 7.0–13.2 times larger than their L2-PBIs; and BlackScholes and Barnes’ L1-PBIs are 84.2 and 733.9 times larger, respectively.

One reason L1-PBI is larger than L2-PBI is the L1 cache has a higher miss rate than the L2 cache due to its smaller capacity. But another reason is the linear scaling of L1-PBI with core count. As the values in parentheses from Table 4 show, every 2x or 4x increase in cores almost always produces a corresponding 2x or 4x increase in L1-PBI. Because L1 caches are private, they do not exhibit the bandwidth reduction benefits from data sharing demonstrated in Section 4.3. In addition, because L1 caches are small, the L1 capacity aggregated across all cores never captures a majority of the benchmarks’ working set. Hence, L1-PBI grows linearly with core count, as shown

	MADD	FFT	LU	KMeans	BlackScholes	Barnes
8C/4MB	1.75	1.77	1.75	1.76	1.74	1.72
32C/16MB	3.88	3.98	3.99	3.85	4.00	3.87
128C/64MB	7.99	8.05	7.94	8.07	8.09	7.94
256C/128MB	10.62	10.58	10.59	11.34	10.85	10.81
256C/64MB	10.60	10.33	10.58	10.60	10.56	10.72
256C/32MB	10.63	10.54	10.61	11.02	10.33	10.64

**Table 5. Average one-way distance (in hops) traveled per L2 reference.**

in Table 4. These results suggest (not surprisingly) the on-chip network will require much higher bandwidth than the off-chip interface.

The last 2 rows of Table 4 show for a given core count (*e.g.*, 256), L1-PBI is fairly insensitive to L2 cache size. This makes sense since the L2 cache has very little impact on the L1 miss rate.<sup>1</sup> Besides the results in Table 4, we also measured L1-PBI for our entire CMP design space (similar to the results in Figure 2), and confirmed L1-PBI always varies linearly with core count and is independent of L2 cache size. We omit the complete set of results for brevity.

Having quantified L1-PBI, we now study the distance traveled by the L1-to-L2 memory requests. As described in Section 3.1, our shared L2 cache distributes cache blocks in a block-interleaved fashion across tiles, effectively randomizing data placement. Because tiles are connected via a 2-D mesh network, one would expect random data placement to cause communication distance to grow as the *square root* of the number of cores. Table 5 reports the average number of hops observed for all L2 references for the datapoints reported in Tables 3 and 4. As Table 5 shows, the communication distance measured in our simulations is consistent with  $\sqrt{P}$  growth. Moreover, communication distance is roughly constant across different applications and L2 cache sizes, which is also consistent with randomized data placement.

Note, Table 5 shows *on-chip physical locality degrades as the number of cores is scaled* due to the simple shared cache organization assumed in our tiled CMP. Had our L2 cache incorporated some of the migration or replication techniques described in Section 2, better physical locality would

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<sup>1</sup>The L2 maintains inclusion which perturbs the L1 contents, but not by much.

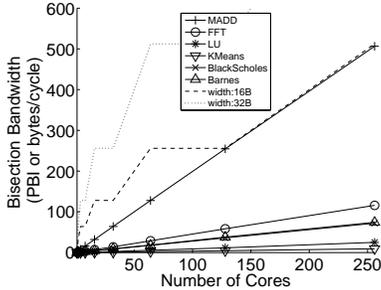


Figure 4. Bisection bandwidth vs. core count.

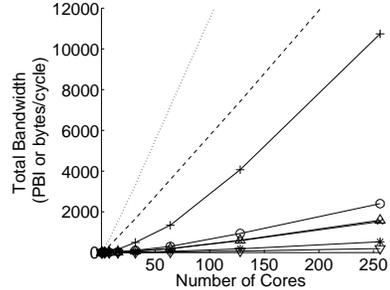


Figure 5. Total bandwidth vs. core count.

likely have resulted despite scaling. This is an important point we will return to in Section 6.

## 5.2 Bandwidth Scaling Analysis

Tables 4 and 5 provide insight into on-chip communication bandwidth scaling. First, bisection bandwidth should scale *linearly* with core count. Because L2 references are destined to random tiles, roughly half of all L2 references should pass through the machine’s bisection. Since the volume of L2 references (L1-PBI) scales linearly with cores, so should bisection bandwidth. Second, total communication bandwidth should scale as  $P^{\frac{3}{2}}$ . Total communication bandwidth is the volume of L2 references (L1-PBI) times the occupancy (number of hops) of each L2 reference in the network. Given L1-PBI grows linearly with  $P$  and per-hop distance grows as  $\sqrt{P}$ , total bandwidth should grow as  $P^{\frac{3}{2}}$ .

To validate these claims, Figures 4 and 5 report the actual simulation results. The solid lines in Figure 4 show the bisection bandwidth for our 6 parallel programs for 1–256 cores.<sup>2</sup> In Figure 4, bisection bandwidth is quantified as PBI (*i.e.*, we measure total traffic through the bisection in bytes, divide by the total number of executed instructions, and multiply by  $P$ ). This data confirms bisection bandwidth does indeed grow linearly with core count. The solid lines in Figure 5 show the total communication bandwidth for our 6 parallel programs using the same format as Figure 4, using PBI as well (*i.e.*, we measure total traffic across all links in the network in bytes, divide by the total number of executed instructions, and multiply by  $P$ ). This data confirms total bandwidth

<sup>2</sup>The total L2 cache size is kept constant at 64MB for these experiments, but this is not important since L2 size does not noticeably impact on-chip traffic.

does indeed grow as  $P^{\frac{3}{2}}$ .

For comparison, Figures 4 and 5 also plot the peak bisection bandwidth and peak total bandwidth, respectively, for each CMP configuration. In particular, the dotted lines plot the peak assuming 32-byte links (used by our simulator), whereas the dashed lines plot the peak for a network with 16-byte links. Peak bandwidth is measured in terms of bytes/cycle, but we plot it along the same PBI Y-axis used by our application results (we will correlate the two in a moment). As Figures 4 and 5 show, both the peak bisection bandwidth and peak total bandwidth scale linearly with core count.<sup>3</sup> Hence, our applications' bisection bandwidth requirements scale at the *same* rate as the peak bisection bandwidth, but their total bandwidth requirements scale *faster* than the peak total bandwidth.

Figures 4 and 5 also indicate for 1–256 cores, there should be sufficient on-chip bandwidth to support our applications. If we assume perfect cores with CPI = 1, then the solid, dotted, and dashed lines can be compared directly (bytes/instruction = bytes/cycle). Even under such optimistic assumptions, all our benchmarks consume significantly less bandwidth (bisection and total) than the peak assuming 32-byte links. Assuming 16-byte links, MADD's bisection bandwidth matches the peak, but all other benchmarks consume significantly less bisection and total bandwidth than the peak. These results show that given moderately sized links, 2-D mesh networks can support the on-chip communication bandwidth requirements of our benchmarks.

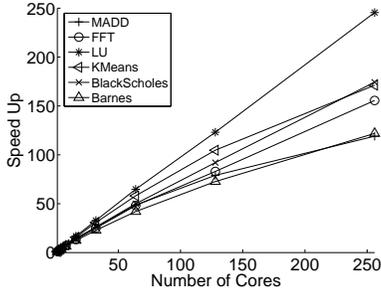
## 6 Performance Evaluation

Sections 4 and 5 study the impact of core and cache capacity scaling on off-chip bandwidth and on-chip communication separately. This section puts everything together by considering overall performance, demonstrating the *relative* impact of the off-chip and on-chip memory overheads.

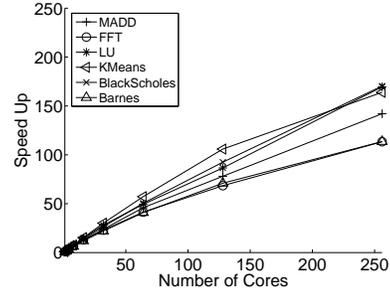
We begin by examining overall speedup. Figure 6 reports speedup assuming *fixed grain-size*

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<sup>3</sup>Bisection bandwidth increases as a staircase because doubling a square 2-D mesh does not change the bisection along the smaller dimension.



**Figure 6. Fixed grain-size speedup (512KB L2-slices).**



**Figure 7. Fixed capacity speedup (128MB L2 size).**

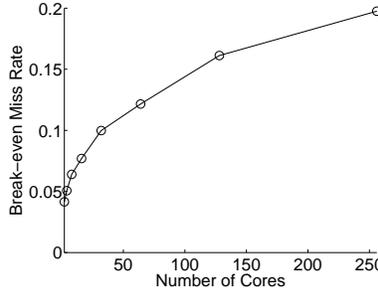
	MADD	FFT	LU	KMeans	BlackScholes	Barnes
1C/512K	0.06	0.31	0.54	0.77	0.71	0.64
4C/2M	0.24	1.16	2.21	2.99	2.64	2.24
16C/8M	0.89	4.14	9.08	12.05	9.85	7.94
64C/32M	2.92	14.91	34.96	44.73	35.42	26.85
256C/128M	7.14	48.22	132.59	131.79	123.70	77.98

**Table 6. IPC achieved by CMP configurations in Figure 6 (*i.e.*, assuming fixed grain-size scaling).**

*scaling* in which L2 slice size is kept constant at 512KB (so total L2 cache grows with scaling), and Figure 7 reports speedup assuming *fixed L2 capacity scaling* in which total L2 size is kept constant at 128MB (so L2 slices shrink with scaling). As Figure 6 shows, speedup under fixed grain-size scaling varies across the different benchmarks. LU achieves the most speedup—up to 245.5 (at 256 cores), BlackScholes, KMeans and FFT achieve moderate speedup—up to 174.2, 171.2 and 155.5, respectively, and Barnes and MADD achieve the least speedup—up to 121.8 and 119, respectively. Program speedups under fixed L2 scaling in Figure 7 show the same trends, but the actual speedup values are smaller due to the improved baseline (1 core with 128MB instead of 512KB L2 cache).

While speedup quantifies parallel performance, the bottom line is absolute performance. Table 6 reports the IPCs achieved by several of the CMPs from Figure 6. As Table 6 shows, IPC is reasonable for LU, KMeans, and BlackScholes, reaching 123+ at 256 cores. But IPC is noticeably lower for FFT and Barnes, reaching only 48–78 at 256 cores, and poor for MADD, never exceeding 10.

To provide insight into the source of poor performance for some of our benchmarks, Figure 9

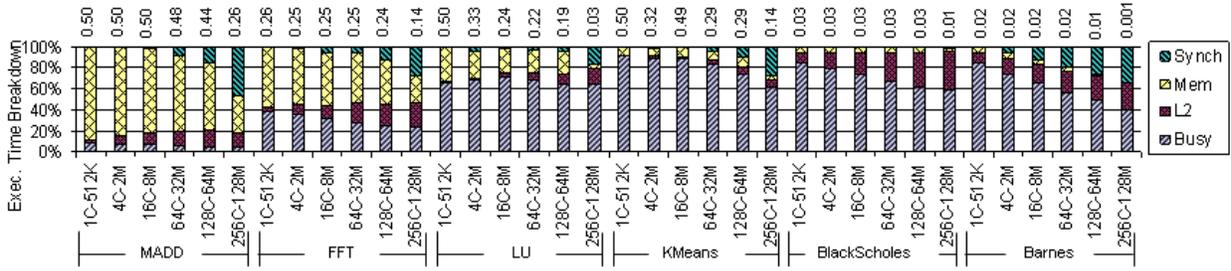


**Figure 8. L2 break-even miss rate vs. core count.**

breaks down execution time into 3 components: executing program code (labeled “Busy”), waiting on L2 cache accesses (labeled “L2”), waiting on off-chip memory (labeled “Mem”), and waiting on synchronization (labeled “Synch”). As Figure 9 shows, synchronization overhead is negligible below 128 cores. At 128 and 256 cores, it becomes more significant—usually around 20%, but as much as 40% (MADD and Barnes). This component is due to load imbalance at barriers. Memory overhead (L2 + Mem) is a more universally significant overhead, accounting for large portions of execution time across most CMP configurations. By 128/256 cores, memory stalls are responsible for 20–81% of the total execution time. (One exception is KMeans where memory stalls account for only 12% of execution time). These results show the memory system is a key bottleneck to parallel performance.

Perhaps more importantly, Figure 9 also shows the relative significance of the off-chip and on-chip memory overheads is application dependent. For BlackScholes and Barnes, access to on-chip memory is the main bottleneck, accounting for 54–99% of all memory stalls. However, for MADD, FFT, LU, and KMeans, access to off-chip memory is the main bottleneck up to 128 cores, accounting for 61–97% of all memory stalls. At 256 cores, MADD is still off-chip limited, but LU and KMeans become on-chip limited. For FFT, the off-chip/on-chip stalls are roughly equal at 256 cores.

These results are due to two conflicting trends at play in Figure 9. On the one hand, on-chip memory overheads grow with core count—*i.e.*, the  $\sqrt{P}$  growth discussed in Section 5.1. On the other hand, off-chip memory overheads decrease with core count and L2 cache capacity—*i.e.*, the



**Figure 9. Execution time breakdown into busy, L2 access, off-chip memory, and synchronization components. L2 miss rate is reported on top of each bar.**

bandwidth reduction due to data sharing and low miss rates discussed in Section 4.3. Both trends are clearly visible in Figure 9. Whether on-chip or off-chip memory overheads contribute more to performance loss depends on the cost of remote cache accesses relative to the L2 miss penalty.

A key observation is the on-chip and off-chip overheads are equal when the L2 miss rate is the ratio of the average on-chip round-trip latency and the L2 miss penalty. At this *break-even miss rate*, L2 requests spend as much time stalled on traversing the on-chip network as they spend stalled on accessing off-chip memory. Figure 8 plots the break-even miss rate for 2–256 cores. For comparison, the labels above each bar in Figure 9 report the L2 miss rate for each benchmark/CMP configuration. Comparing Figures 8 and 9, we see that indeed off-chip overheads dominate when the L2 miss rate is above the break-even miss rate, while on-chip overheads dominate when the L2 miss rate is below the break-even miss rate.

Another factor is contention. In general, contention at the off-chip interface is more significant than contention across the on-chip mesh network. At 256 cores, we observe 30% of main memory requests in MADD and FFT encounter contention at the memory controllers, while for the remaining benchmarks, contention occurs for 2-6% of main memory requests. In contrast, we see essentially no contention at all in the on-chip network. (These results are consistent with the analysis for Figures 4 and 5).

While Figure 9 shows both off-chip and on-chip memory overheads are significant, we note the

break-even miss rates in Figure 8 are not large, reaching only 20% for 256 cores. This implies memory-intensive programs will most certainly be off-chip limited. Even for our benchmarks, the majority of CMP configurations are off-chip limited, not on-chip limited—and this would be the case even more so had we chosen larger input problem sizes. Moreover, with more aggressive cores (*e.g.*, out-of-order execution and/or prefetching) creating greater memory bandwidth pressure, the imbalance between off-chip and on-chip contention would likely be further amplified, again making off-chip overheads relatively more significant. We find this is a surprising result, especially given the simple shared L2 cache we assume and its poor scaling of on-chip physical locality with core count.

## 7 Conclusion

This paper conducts an in-depth study of LCMP scalability for parallel programs, providing insight into the impact of core count and cache capacity scaling on off-chip bandwidth and on-chip communication. Our results show off-chip bandwidth often increases linearly with core count; however, for parallel programs with data sharing, the rate of bandwidth increase reduces dramatically once enough L2 cache is provided to capture the inter-thread sharing references. In addition, our results also show for the range 1–256 cores, there should be ample on-chip bandwidth to support the communication requirements for all our benchmarks given moderately-sized network links. Finally, we find that when an application’s L2 miss rate is larger (smaller) than a break-even miss rate, it becomes off-chip (on-chip) limited. For memory-intensive programs and LCMPs with aggressive cores, we expect off-chip memory overheads to dominate on-chip memory overheads, even when the LLC provides no explicit on-chip locality management.

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