1 Summary

Stata/MP\(^1\) is the version of Stata that is programmed to take full advantage of multicore and multiprocessor computers. It is exactly like Stata/SE in all ways except that it distributes many of Stata’s most computationally demanding tasks across all the cores in your computer and thereby runs faster—much faster.

In a perfect world, software would run 2 times faster on 2 cores, 3 times faster on 3 cores, and so on. Stata/MP achieves about 75% efficiency. It runs 1.7 times faster on 2 cores, 2.4 times faster on 4 cores, and 3.2 times faster on 8 cores (see figure 1). Half the commands run faster than that. The other half run slower than the median speedup, and some of those commands are not sped up at all, either because they are inherently sequential (most time-series commands) or because they have not been parallelized (graphics, mixed).

In terms of evaluating average performance improvement, commands that take longer to run—such as estimation commands—are of greater importance. When estimation commands are taken as a group, Stata/MP achieves an even greater efficiency of approximately 85%. Taken at the median, estimation commands run 1.9 times faster on 2 cores, 3.1 times faster on 4 cores, and 4.1 times faster on 8 cores. Stata/MP supports up to 64 cores.

This paper provides a detailed report on the performance of Stata/MP. Command-by-command performance assessments are provided in section 8.

Figure 1. Performance of Stata/MP. Speed on multiple cores relative to speed on a single core.

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3 Introduction

Stata/MP was designed to take advantage of computers with multiple cores and multiple processors by partitioning the work among the multiple cores. From the outset, Stata/MP was required to be 100% compatible with all other flavors of Stata, including Stata/SE and Stata/IC. Stata/MP was also required to run all scripts, user-written programs, and analyses that run under existing Stata without any change or special action on the user’s part.

Stata/MP runs on multicore and multiprocessor computers, including computers running MS Windows (2000, XP, 7, 8, and later), Intel-based Mac OS computers, Linux computers, and 64-bit computers running Oracle Solaris.

With multiple cores, one might expect to achieve the theoretical upper bound of doubling the speed by doubling the number of cores—2 cores run twice as fast as 1, 4 run twice as fast as 2, and so on. However, there are three reasons why such perfect scalability cannot be expected: 1) some calculations have parts that cannot be partitioned into parallel processes; 2) even when there are parts that can be partitioned, determining how to partition them takes computer time; and 3) multicore/multiprocessor systems only duplicate processors and cores, not all the other system resources.

Stata/MP achieved 75% efficiency overall and 85% efficiency among estimation commands.

Speed is more important for problems that are quantified as large in terms of the size of the dataset or some other aspect of the problem, such as the number of covariates. On large problems, Stata/MP with 2 cores runs half of Stata’s commands at least 1.7 times faster than on a single core. With 4 cores, the same commands run at least 2.4 times faster than on a single core.

Figure 1, shown in the summary above, displays the theoretically possible performance as a shaded region. All Stata commands fall somewhere in the shaded region. Performance is measured as speed relative to speed on a single core: 1 indicates the speed on a single core; 2 means twice as fast as a single core; 4 means four times as fast as a single core; and so on. We could say the same thing in a different way: 2 means that a given problem runs in half the time required on a single core; 4 means that it runs in one-quarter the time; and so on.

The line in figure 1 for logistic regression reveals a speedup that is near the theoretical maximum. At the other end of the spectrum, some Stata commands experience no speedup at all. This is because their calculations are inherently sequential or because no effort was made to partition the work into parallel processes.

In typical use, Stata’s estimation commands consume the bulk of the time required to perform analyses, so speeding them up was a priority for Stata programmers. Figure 1 also shows the median performance of Stata’s estimation commands. The median estimation command runs 1.9 times faster on 2 cores and 3.1 times faster on 4 cores. Again, half the estimation commands speed up more than the median and half speed up less. Twenty-five percent of estimation commands speed up 2 times with 2 cores (the theoretical limit) and more than 3.7 times with 4 cores (this is not shown on the graph).

Figure 1 emphasizes dual-core, quad-core, and 8-core computers because those are the most common multicore platforms available. Stata/MP will work with up to 64 cores, however, and performance improvements continue to increase with more cores. For example, 25% of estimation commands run
at least 6 times faster on 8-core computers, 10 times faster on 16-core computers, 15 times faster on 32-core computers, and 19 times faster on 64-core computers.

For assessments of performance gains of individual Stata commands, see section 8. See appendices A and B for results reported in graphical form.

4 Parallel computing hardware

Chip makers are increasing the number of cores on a computer processor, and computer makers are increasing the number of processors in a computer. Prior to 2005, chip makers essentially doubled the speed of computer processors every 18 months, a fact known informally as Moore’s law (Moore 1965). The speed improvements were achieved by making components smaller—hence reducing electrical resistance—and by placing more transistors on a processor. Chip makers, however, are reaching the physical limits of what can be achieved through reduced size and increased complexity using existing technology. Although alternatives for further speeding up processors are on the horizon, these alternatives involve dramatic changes in technology and fabrication.

The other alternative to make computers run faster is simply to give you more processors or cores.

Modern computers run faster by having multiple processors in one box or multiple processors on one chip. When multiple processors are on one chip, the chip makers call such processors cores, and the chip they reside on is called a multicore processor. Each core is itself a processor that is bundled together with other cores onto a single chip.

Regardless, when they reside together in one box, all the processors and cores share the main memory, disk drives, and other devices on the computer. Most modern computers use multicore processors. Modern servers typically use multiple processors, each having multiple cores. Whether the cores are on one processor chip or on multiple processor chips does not much matter.

Following the lead of the chip makers, we are going to count cores and talk about cores on a computer. We are also going to use the term multicore to include both a single-processor computer whose processor has multiple cores and a multiprocessor computer whose processors also may have multiple cores.

Multicore designs work exceptionally well when running different programs simultaneously, especially when programs run independently. Hence, a 4-core computer can do almost as much work as four separate computers, and none of the programs needs to be modified to recognize that it is running in a multicore environment.

Single programs can take advantage of multicore environments, too, but the programs must be modified to do so. This modification is accomplished by allowing different parts of the program to run simultaneously in what are called separate execution threads. For example, a word processor might allow you to print and edit a document simultaneously. This type of threading is relatively easy to implement and is even allowed on single-core computers to make programs more convenient.

This type of threading adds convenience but does not address the issue of speeding the computations in a statistical package. To speed computations, a statistical package must be able to perform simultaneous computations on the same task. This ability is referred to as symmetric multiprocessing.
(SMP). Stata/MP is a modified version of Stata that uses SMP to speed up its computations.

Another type of parallel processing involves using multiple computers over a network. This type is known as cluster computing or distributed computing. Cluster computing requires problems that admit large-grain parallelization. Although cluster computing can be of interest in the computation of statistical results, Stata/MP does not address such parallel architectures.

For a thorough discussion of parallel processing, see Culler, Singh, and Gupta (1999) and Grama et al. (2003).

5 Constructing Stata/MP

For Stata to take advantage of multicore systems, sections of its code had to be rewritten to distribute their work across cores. Stata’s internal design includes key algorithms that are used in many contexts. Once those key algorithms were rewritten, the benefits then spread themselves across Stata. Statistical computations lend themselves especially well to parallelization because observations are usually independent, and independent pieces can be calculated separately. One way parallelization happens is that many statistical computations can be partitioned over observations.

Parallelizing key algorithms resulted in a little more than half the observed performance gains. The remaining gains were achieved by modifying individual routines for important Stata commands and including custom code to parallelize them.

In all, approximately 250 sections of Stata’s internal code were parallelized using the Open/MP API for developing SMP applications (see Dagum and Menon [1998]).

6 Measuring Stata/MP’s performance

There is a theoretical limit to how much the performance of a program or command can be improved with multiple cores (or processors). With 2 cores, that limit is twice as fast (or half the run time); with 4 cores, the limit is 4 times as fast (or one-quarter the run time); and so on. This limit is called linear or perfect scaling.

Furthermore, not all algorithms or sections of code can be made to run in parallel. Some computations, or parts thereof, are inherently single threaded, for example, a formula that depends on prior values of itself, such as the autoregressive process:

\[ y_t = \phi + \rho y_{t-1} \]

Statistical calculations are often more parallelizable than you might imagine. For instance, many inherently sequential computations can be parallelized when performed on longitudinal (panel) data because the dependencies that made the problem inherently sequential are broken at panel boundaries. Rather than partitioning on observations, Stata/MP partitions on panels. Whereas most time-series
commands run only a little faster in the SMP environment, most panel-data commands run substantially faster.

Some sections of code are simply not worth the effort of parallelization because they take so little time to run or because parallelization would be technically difficult. Either way, the effort is just not worth the benefit.

Taken together, those sections of code are the nonparallelized region. Some authors refer to the parallelizable regions and the parallelized regions—the first referring to what could be parallelized and the second to what was actually parallelized—and even focus on the ratio between the two. We will focus on run times and their associated relative speeds, however, and draw no distinction between parallelizable and parallelized.

How much of a calculation has been parallelized is measurable, and measuring it is useful because it allows us to make extrapolations on how problems will run when the number of cores varies.

Figure 2 presents a stylized view of the component run times associated with a command that has been parallelized. Block A represents the time spent in parallelized regions of code; Block B, the unparallelized regions of code; and Block C, the additional overhead required for parallelization.

Like each letter represent an amount of time consumed in running a particular command on a particular dataset. Then $A + B$ is the run time of the command when using a single core. If we parallelize the command, however, there is an additional time, $C$, associated with the overhead of partitioning the problem and coalescing the results from the cores.

Figure 2. Parallelization components.
If we know the percentage of time spent in \(A\), then we have completely described the SMP performance of a command. Ignoring \(C\), that is just \(100A/(A + B)\).

We want to be more conservative, however, and account for the time required to parallelize the command. Considering \(C\) to be only the parts of the overhead that cannot be parallelized, we will refer to \(100A/(A + B + C)\) as the percentage parallelized:

\[
\text{percentage parallelized} = \frac{100A}{A + B + C}
\]

The percentage parallelized is a useful measure of how much performance will improve as cores (or processors) are added. All gains to parallelization occur because region \(A\) can be made to run on multiple cores at the same time. If we partition the region perfectly and each core runs uninterrupted, then when we double the number of cores, we halve the time used to perform \(A\). As we add more cores, time spent in \(A\) continues to decrease. With 2 cores, it is \(A/2\); with 4 cores, it is \(A/4\); and with \(c\) cores, it is \(A/c\). If we increase the number of cores without bound, \(A/c\) goes to zero. In contrast, \(B + C\) is a constant time for running the command; it cannot be reduced by adding more cores. As we add cores, the run time asymptotes to \(B + C\).

We are ignoring another minor contribution to run time. Sometimes, overhead is associated with each core rather than, or in addition to, an overall parallelization overhead. Because of the methods used to build Stata/MP, this overhead is extremely small. In fact, it affects only four commands, and its effect on them is small.

The concept of percentage parallelizable helps clarify why some commands will have less-than-perfect scaling and allows results to be extrapolated to any number of cores. We also present performance results as simple relative speeds that can be read directly from tables or graphs to find the relative speed for multiple cores or processors compared with the speed for a single core or processor.

7 Performance summary

The performance of Stata/MP has been measured on 529 Stata commands. Excluding I/O commands, these 529 commands are most of the commands that take any appreciable time to run. Commands such as display (which writes output to the Results window) or local (which sets the value of a program macro) are not considered because they consume a negligible part of the time required to perform any analysis. Commands that run a target command repeatedly are not explicitly assessed, and some other commands are not timed for a variety of reasons; see appendix E. If you are searching this document for a specific command, know that we have tried to list every Stata command somewhere in the paper.

For each of the 529 commands, timings were recorded on a multicore computer where Stata/MP used 1, 2, \ldots, 40 cores to execute the same command. The computer contained four processors, each having 10 cores, for a total of 40 cores. All these timings were from the same installation of Stata/MP on the same computer. To reduce the impact of interruptions by the operating system, the timings were repeated three times and the shortest time was recorded.

Timings have also been performed on other dual-core, quad-core, 8-core, and 16-core computers.
Although speeds relative to a single core do vary among tested platforms, they are generally comparable, and the results presented are indicative of what can be expected across a spectrum of platforms. The results of the timings are presented in section 8, Stata/MP performance, command by command, and appendix A, Performance assessment graphs for desktop computers.

Appendix A, Performance assessment graphs for desktop computers, shows graphs for each of the 529 commands. Figure 3 shows the graph of Stata’s logistic regression command, logistic:

Figure 3. logistic performance plot.

The $y$ axis shows speed relative to the speed on a single core. For logistic, the relative speeds are 2 (2 cores), 3.8 (4 cores), and 6.9 (8 cores). Also shown is a 45° reference line representing perfect scalability or, if you prefer, 100% parallelized: 2 times (2 cores), 4 times (4 cores), and 8 times (8 cores). logistic is 98% parallelized, but even so, you can see that its relative speeds are a bit below what is theoretically possible.

Stata’s linear regression command, regress, very nearly achieves theoretical limits (see figure 4); its relative speeds increase in almost direct proportion to the number of cores.
Figure 4. `regress` performance plot.

Figure 5 shows the graph for `arima`:

Figure 5. `arima` performance plot.

`arima`, a time-series command, hardly benefits from parallelization. Relative speeds are 1 (2 cores), 1 (4 cores), and 1.1 (8 cores).
Figure 6 shows the graph for Stata’s command for Poisson regression with endogenous treatment effects, `etpoisson`:

Relative speeds are 1.6 (2 cores), 2.2 (4 cores), and 2.9 (8 cores). What is interesting about this graph is that the line flattens out as the number of cores increases. This is what happens when a command is not 100% parallelized: the relative run time approaches a horizontal asymptote that is related to the percent parallelized, which here is about 50%. Specifically, the asymptote is at $1/(1 - \text{(percentage parallelized)}/100)$, which for `etpoisson` is about 2.

Finally, all 529 performance profiles can be combined into one figure, such as figure 7. The shaded area shows the region containing all possible performances. The diagonal top of the region represents perfect scaling (the maximum speed theoretically possible), while the horizontal lower boundary of the region represents no speed improvement.
Figure 7. **Performance of Stata/MP.** Speed on multiple cores relative to speed on a single core.

Also included are the median results over all 529 commands; 264 commands have better performance gains (their curves lie above the median relative speedup line), and 264 exhibit lesser performance gains (their curves lie below the line).

Median performance for most Stata users will be better than median performance across commands as we calculated it. To be able to measure performance, we had to choose large problems even when, for a particular command, large problems are rarely run. For instance, few users would run analyses that spend as much time running $t$ tests as did those analyses we had to run to record reliable results. Stata’s command for $t$ tests runs quickly on single or multiple cores. Meanwhile, Stata/MP development efforts focused on improving run times of commands that require substantial run times. Ergo, the median improvements are understated.

Figure 8 better illustrates the distribution of results by showing not just the median but also the quartiles. The most interesting thing about figure 8 is the first quartile (light-blue swath at the top). It shows that 25% of commands exhibit nearly perfect scaling. The worst commands among this group run about 2 times faster on 2 cores, 3.7 times faster on 4 cores, and 6.4 times faster on 8 cores.
Figures 7 and 8 present results for all commands, whereas the time required by most analyses is dominated by execution of estimation commands. Estimation commands tend to be the most computationally intensive, particularly those that require iterative solutions.

Figure 9 summarizes the observed performance and median performance for the 284 estimation commands. These include all the estimation commands in Stata, and some commands are included more than once to include critical options, such as `vce(robust)` and `vce(cluster)` for robust standard errors and correlation within groups. The options themselves are not important; what is important is that these options and a few others like them substantively affect how the calculation proceeds and thus affect speed.

Compared with figure 7, figure 9 shows that the median performance for estimation commands is better than the overall median. The median relative speed for estimation commands is 1.9 times faster on 2 cores, 3.1 times faster on 4 cores, and 4.1 times faster on 8 cores. Half of all estimation commands perform even better. Figure 10 reveals that only 25% of all estimation commands run less than 1.5 times faster on 2 cores, less than 2.1 times faster on 4 cores, and less than 2.6 times faster on 8 cores.
We have emphasized results on 2, 4, and 8 cores because those are the most common desktop architectures currently available. Stata/MP supports up to 64 cores, and performance continues to improve as cores are added. Figure 11 shows the performance boundary and median for all 284 estimation commands on 1–40-core computers, and figure 12 shows their performance quartiles.

![Figure 9. Performance of Stata/MP on estimation commands.](image1)

![Figure 10. Quartiles of Stata/MP performance on estimation commands.](image2)
8 Stata/MP performance, command by command

The performance summaries from the prior section provide an overall sense of the performance of Stata/MP but will not reflect the experience of most users. Few users perform all the commands in Stata, and no users perform them with equal frequency. Most users will be interested in a subset of commands and often in only a few commands that they use regularly on large problems.

Table 1, toward the end of this section, provides relative speeds on individual commands, comparing the speed on 2, 4, 8, and 16 cores with the speed on a single core. The table also reports the degree to which each command is parallelized.

All commands were run on moderately-large-to-very-large problems. The goal was to measure performance on problems that required substantial time to solve and that were large enough to measure performance gains on 8, 16, 32, or even 64 cores. For commands that are parallelized, such problems have a larger parallelizable region ($A$) relative to the unparallelizable region ($B$) and are thus more amenable to parallelization, particularly when run on many cores. Longer timings also ameliorate variations in timings, such as interruptions caused by operating system processes or the memory status of the system when the command begins. Run-to-run variations are much greater for smaller problems that have shorter run times.
Timings were typically performed on commands that took 1–2 minutes to run on a single-core computer running at 2.2–3.4 GHz. For some commands, this meant that the problems used extremely large numbers of observations or covariates, because some commands are inherently fast. For others, the problems were smaller because the commands are inherently slow, because of, for example, iterative or even simulated solutions. For details on the sizes of the problems, see appendix D.

Stata/MP was designed mostly to improve performance on large problems, such as those reported in appendix D. Even so, the performance on small-to-moderate problems improves surprisingly well. Using the same commands as those in appendix D, but with problems 100 to 10,000 times smaller and run times of 0.4 seconds to just over 4 seconds on a machine running at 2.2–3.4 GHz, substantial speedups were still observed. Among commands that were at least 50% parallelized, more than half exhibited greater than 90% of the speedup exhibited on the larger problems. These are typical results. Run times for smaller problems vary more from computer to computer because small problems are more sensitive to the architecture of the computer, processor, and operating system.

All values were obtained from the minimum of three runs on a 40-core computer.

Stata/MP performance was tested on many computers under MS Windows, Mac, Linux, and Oracle Solaris operating systems. Although performance varies somewhat across platforms, the results from the table below can reasonably be applied to any platform.

Most users should simply look at the column reporting results for the number of cores in which they are interested. This column estimates the speed on that number of cores relative to the speed on a single core. Given a computer with a known number of cores, this column of results is the most direct measure of performance improvement.

Relative speed is easy to understand. When relative speed is 2, you could run a given problem twice in the same amount of time that you could run it once on a single-core computer. When relative speed is 4, you could run a given problem four times, and so on. Equivalently, when relative speed is 2, you could run a given problem in half the time that you could run it on a single-core computer. When relative speed is 4, you could run a given problem in one-fourth the time, and so on.

Table 1 also presents the percentage parallelized discussed in section 6. Given a set of percentage run times (relative to the run times on a single core) for at least 3 different numbers of cores, we can estimate the percentage parallelized and parallelization overhead parameters. The form of the model is particularly simple:

$$\text{percentage run time} = \alpha + \frac{PP}{c} + \frac{O}{c} \delta_1$$  \hspace{1cm} (1)

where \(c\) is the number of cores, \(\delta_1\) is an indicator for \(c > 1\), and \(\alpha\) is an intercept.
Our parameters of interest are directly estimated:

\[
\text{percentage parallelized} = \hat{PP} \tag{2}
\]

and

\[
\text{parallelization overhead} = \hat{O} \tag{3}
\]

Equation (1) is estimated by median regression (\texttt{qreg}) using Stata. Median regression is used in preference to ordinary least squares (OLS) because occasionally a timing will be far too large because of interruptions from the operating system. Such effects are ignored in median regression.

The estimated value for parallelization overhead is particularly sensitive to the computing platform, and so we do not report it here. Note from equation (1) that \(\hat{O}\) captures any unexpected difference in the speed when using one core. Because different computer, processor, cache, and operating system architectures respond differently in moving from 1 to 2 cores, \(\hat{O}\) captures not only the theoretical parallelization overhead, but also anything that causes the time from the first core to differ from the time from the second.

Percentage parallelized is the most concrete measure of how a command responds to more cores. For most commands, the run time in this percentage of the code falls by half for each doubling of the number of cores.

The estimated percentage parallelized is also the most comparable measure across computing platforms; it is very consistent from one platform to another. Most of the differences across computing platforms are captured in \(\hat{O}\). Because the relative speeds are compared with the run time on a single core, they necessarily include the parallelization overhead and are thus not quite as comparable across machines.

Each line in the table represents a command run on a particular problem. The command column shows the Stata command name and relevant options. For those unfamiliar with Stata syntax, appendix C provides short descriptions of what each command does. To learn more about any command, including worked examples, all of the Stata manuals can be access from \url{http://www.stata.com/features/documentation/}.

Appendix A contains performance graphs for each command using 1–8 cores. Appendix B contains graphs using 1–40 cores. The graphs plot the observed relative speed, the modeled performance using equation (1), and the perfect scalability reference line. If you are reading the PDF version of this document, you can click on the command name in table 1 to go to the page with the associated graph.
Table 1. Stata/MP performance, command by command

<table>
<thead>
<tr>
<th>Command</th>
<th>Number of cores</th>
<th>Percentage parallelized</th>
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<tbody>
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<td></td>
<td>2</td>
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<td>alpha</td>
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<td>ameans</td>
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<td>anova (two-way)</td>
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<td>arch</td>
<td>0.9</td>
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<td>areg</td>
<td>2.5</td>
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<td>areg, vce(cluster)</td>
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<td>3.5</td>
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<td>areg, vce(robust)</td>
<td>2.1</td>
<td>3.7</td>
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<td>asclogit</td>
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<td>asmprobit</td>
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<td>biprobit</td>
<td>1.9</td>
<td>3.7</td>
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</table>

All values are expressed as the speed relative to the speed of a single core.

a. Bigger is better; 2 is perfect for 2 cores, 4 is perfect for 4 cores, 8 is perfect for 8 cores, and 16 is perfect for 16 cores.

b. Bigger is better; 100 is perfect.
### Table 1. Stata/MP performance, command by command

<table>
<thead>
<tr>
<th>Command</th>
<th>Number of cores</th>
<th>Percentage parallelized</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td><strong>biprobit (seemingly unrelated)</strong></td>
<td>2.0</td>
<td>3.9</td>
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</table>

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<table>
<thead>
<tr>
<th>Command</th>
<th>Speed relative to a single core(^a)</th>
<th>Number of cores</th>
<th>Percentage parallelized(^b)</th>
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</table>

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<thead>
<tr>
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<th>8</th>
<th>16</th>
<th>Percentage parallelized</th>
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<td>streg, distribution(gamma)</td>
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<td>streg, distribution(weibull)</td>
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<th>Percentage parallelized&lt;sup&gt;b&lt;/sup&gt;</th>
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<th>Percentage parallelized(^b)</th>
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b. Bigger is better; 100 is perfect.
Nine of the lines in table 1 represent estimation commands run on survey data. Each of these commands begins with `svy`. These are only a few of the estimation commands that support estimation on survey data, but we can make some generalizations about how the three primary methods of estimation with survey data will perform with other estimation commands. With the linearization method, prefix `svy linearized`, estimation commands will be parallelized just as well and sometimes better than they were parallelized on non-survey data. This is true because the linearization computation is itself almost 100% parallelized. When using the balanced repeated replications (BRR) method, `svy brr`, or the jackknife method, `svy jackknife`, almost all estimation commands are slightly less parallelized. The BRR and jackknife VCE computations are not themselves parallelized, but the overall estimation time is dominated by standard estimation.

More than a full page of table 1 is dedicated to performance when using multiple imputation (MI). These commands begin with the `mi` prefix. All the results in the table are from problems with five imputations. The number of imputations does not affect parallelization performance much. As with all commands, problems with more observations and covariates are better parallelized; see appendix D for the sizes of problems used to assess performance.

There are two particularly computationally intensive aspects to using MI data—creating the MI datasets (imputation) and estimation. The table reports the results for all the primary methods of imputation; these lines are prefixed with `mi impute`. It also reports the results for four representative estimators—linear regression (`regress`), logistic regression (`logit`), multinomial logistic regression (`mlogit`), and ordered logistic regression (`ologit`).

Performance on MI data is affected by the style in which the MI data are stored. Stata allows four styles for storing MI data: wide (`wide`), marginal long (`mlong`), full long (`flong`), and full long and separate (`flongsep`). Each style has advantages with regard to storage required and ease of use in some analyses.

With regard to imputation performance under Stata/MP, imputation is fastest and most parallelized when using style `flongsep`. `flongsep` is the native style in which imputations are performed. Table 1 reports performance across all MI storage styles for only the `logit` imputer; the relative performance of the styles is similar for other imputers.

Estimation is fastest and most parallelized when using storage style `wide`, although style `flongsep` is also well parallelized. Style `wide` is fastest because the overhead for managing `wide` data mostly involves simply changing the names of variables. The table reports estimation results in all four MI storage styles for only `regress` and `logit`. The relative performance is similar for other estimators.

As with estimation using survey data, MI can be applied to many more estimation commands than those listed in the table. Only some of the MI computations are themselves parallelized, so most commands are less parallelized when used with MI data, regardless of the style in which the data are stored. Computationally intensive estimation commands that involve iterative solutions, such as logistic regression, are less affected than are commands with closed-form solutions, such as linear regression.

For maximum performance using Stata/MP, set the MI storage style to `flongsep` when performing imputations and to `wide` when performing estimations. The short time you invest to convert between styles will be more than repaid in faster imputation and estimation. If you have insufficient memory to store an MI dataset in style `wide`, then continue to use `flongsep` during estimation.

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When using many imputations on moderate-to-small problems, the overhead of the MI computations can dominate the time required. Such problems are less parallelized than reported in the table. Conversely, very large problems with few imputations are parallelized even more than reported in the table.

9 Performance variability across computing platforms

As discussed in sections 3 and 4, multicore/multiprocessor performance will vary across computing platforms for many reasons. Those reasons include differences in how operating systems partition tasks, how processors pipeline and partition instructions, how memory is accessed, and how onboard processor cache is handled.

Stata/MP performance has been tested on dozens of different platforms, including different processors (both Intel and AMD), different cache architectures, different operating systems (including Microsoft Windows, Mac OS X for Intel, Linux, and Oracle Solaris), and different architectures for accessing memory. Despite the possibility for varying performance, the results from all these tests support the results presented in section 8 and appendixes A and B.

It is not helpful to break these results down by platform. There were no conclusive patterns among operating systems, CPUs, or other platform characteristics.

10 Hyperthreading—single- and multiple-processor platforms

Hyperthreading is an Intel technology for allowing each core of a processor to masquerade as two cores. The operating system and other applications see each physical core as two virtual cores and treat each just as they would any physical core. Intel achieves performance improvements primarily because main computer memory is slow compared with the processor and its onboard cache memory. When the execution thread of one process must wait for something from main memory, the thread for another process can execute. The effect is clearly not the same as having two cores, but for many applications, performance can be improved by treating a computer with a hyperthreaded processor as having twice as many cores as it actually has.

Stata/MP runs on hyperthreaded processors.

Most Stata commands are computationally intense and Stata/MP has been optimized to access main memory efficiently. For these reasons, we would not expect hyperthreading to substantially improve the performance of most commands. Our timings indicate that this is true for most Stata commands, but a few performance gains were surprisingly good.

Figure 13 presents the now familiar boundary region and median performance of Stata/MP running on a quad-core computer with hyperthreading – making for 8 virtual cores. Through the first 4 cores, performance is almost identical to what we saw in Figure 7 for a non-hyperthreaded processor. That is to say, so long as we do not exceed the number of physical cores on a system, hyperthreaded computers behave just like non-hyperthreaded computers.
Above 4 cores, median performance drops for 5 cores, one of them virtual, but improves to approaching the performance of 4 physical cores. The most interesting point beyond 4 cores is 8 cores — all of the virtual cores on the computer. The median relative speed with 8 cores is 2.2, which is slightly less than the median speed of 2.3 for the 4 physical cores.

Figure 14 presents the quartiles of command performance. The diagonal top of the light-blue region indicates that at least one command has perfect parallelization over all 8 virtual cores. Moreover, for the 25% of commands that perform best with hyperthreading their relative speed is at least 3.8 with all 8 virtual cores as compared to 3.6 with 4 physical cores — a 5% improvement. At the other end of the spectrum, for the 25% take the least advantage of hyperthreading, the performance on 8 virtual cores is worse than that of 4 physical cores.

By way of caution, Stata/MP has not been evaluated on a wide range of single-processor hyperthreaded computers, and these results should therefore be considered provisional.

On multiprocessor computers where each CPU is hyperthreaded, the current recommendation is to set Stata/MP to use the number of real CPUs, not the number of virtual processors. Under such architectures, each CPU appears to Stata/MP and the operating system as two processors, and Stata/MP would by default try to use all the (virtual) processors. On these computers, users should type

```
. set processors #
```

where # is the number of CPUs on the computer. Here we use “CPU” to mean a physical core on the computer and not a virtual core created by hyperthreading. So, we could equivalently say, where # is the number of physical cores on the computer.
This can be done either interactively or placed in Stata’s `profile.do` startup script.

Current experience indicates that setting the number of processors to be used above the number of real CPUs on the computer leads to contention for the floating-point unit (FPU), which can make commands run slower when trying to use virtual processors.

Figures 15 and 16 show the results of two commands run on an 4-processor computer, each hyper-threaded, giving the appearance of 8 virtual processors.

![Figure 15. `predict, leverage` performance plot on computers with hyperthreaded CPUs.](image1)

![Figure 16. `regress` performance plot on computers with hyperthreaded CPUs.](image2)

The `predict, leverage` command, however, is an exception to this recommendation. This command remains nearly perfectly parallelized through all 8 processors (half of which are virtual).

Most commands do not exhibit results like this, and `regress` is an example. Beyond the number of real CPUs, performance actually degrades. This occurs because each CPU has only one FPU, and `regress`, along with most Stata commands, requires many floating-point computations. The computations are dominated by access to the FPU, and the virtual processors must contend for access to this single FPU.
A  Performance assessment graphs for desktop computers

The performance of Stata/MP as reported in columns 2, 3, and 4 of table 1 is presented graphically below, along with the modeled performance from equation 1 and a line representing perfectly scalable performance.

Figures 17 and 18 show two typical graphs. As with table 1, performance is measured as the speed of executing the command on multiple cores relative to the speed on a single core.

For a perfectly scalable command, the speed doubles each time the number of cores is doubled. This type of scalability is linear when the number of cores and the relative speed are graphed on a logarithmic scale, which is the scale used in these graphs. Perfect scaling is shown on each graph as a green line that diagonally bisects the graph.

Linear regression, shown in figure 17, is nearly perfectly scalable. Both the observed values and the modeled performance are nearly on the perfect-scalability reference line. The speed is doubled each time the number of cores doubles.

As shown in figure 18, conditional logistic regression clearly performs better as the number of cores increases, but not as much better as linear regression. From table 1, we can see that \texttt{clogit} (1 to k matching) is 68% parallelized as compared with 100% for \texttt{regress}. From figure 18, we see that \texttt{clogit} run with 2 cores on a large dataset is 1.5 times faster than when run with one core; with 4 cores, this relative speed climbs to 2; and with 8 cores, it climbs further to 2.4.

Figure 8, from section 7, summarizes the information from all the graphs in this section by placing the observed performance for each command into one of the performance quartiles on the graph.
In a few of the graphs that follow, the observed performance exceeds the theoretical limit of perfect scaling—some of the relative speeds are above the diagonal perfect-scaling line. An example of this can be seen when the \texttt{replace} command is evaluating small expressions, as shown in figure 19.

![Graph showing performance comparison]

Figure 19. \texttt{replace} performance plot.

This phenomenon is nothing more than a cache effect. Cache is very high speed memory that processors use to store data and code that they use often or expect to use often. Cores run much faster when the data they need can be found in cache rather than in standard memory. The \texttt{replace} command above was able to find far more of the data it needed in cache when running on 2 or more cores than it could find when running on a single core. The model that we used to determine percentage parallelized ignored that cache effect and correctly determined that the \texttt{replace} command was just under 100% parallelized, not greater than 100%.

Observant readers will have noted that the \texttt{regress} command in figure 17 exhibited some mild cache effects. Its observed performance is slightly above perfect scaling.
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Figure 21. **ameans** performance plot.

Figure 22. **anova** (one-way) performance plot.

Figure 23. **anova** (two-way) performance plot.
Figure 24. arch performance plot.

Figure 25. areg performance plot.

Figure 26. areg, vce(cluster) performance plot.

Figure 27. areg, vce(robust) performance plot.
Figure 28. \texttt{arfima} performance plot.

Figure 29. \texttt{arima} performance plot.

Figure 30. \texttt{asclogit} performance plot.

Figure 31. \texttt{asmprob} performance plot.
Figure 32. asprobit performance plot.

Figure 33. bayesmh logit performance plot.

Figure 34. bayesmh mvn performance plot.

Figure 35. bayesmh mylogit performance plot.
Figure 36. `bayesmh nl` performance plot.

Figure 37. `bayesmh normal` performance plot.

Figure 38. `bayesmh normal gibbs` performance plot.

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Figure 43. `biplot` performance plot.
Figure 44. **biprobit** performance plot.

Figure 45. **biprobit** (seemingly unrelated) performance plot.

Figure 46. **bitest** performance plot.

Figure 47. **blogit** performance plot.
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Figure 52. `bstat` performance plot.

Figure 53. `by: generate` performance plot.

Figure 54. `by: generate` (small groups) performance plot.

Figure 55. `by: replace` performance plot.
Figure 56. by: replace (small groups) performance plot.

Figure 57. ca performance plot.

Figure 58. candisc performance plot.

Figure 59. canon performance plot.
Figure 60. *cc* performance plot.

Figure 61. *by: cc* performance plot.

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Figure 63. *churdle linear* performance plot.
Figure 64. ci means performance plot.

Figure 65. ci means, poisson performance plot.

Figure 66. ci proportions performance plot.

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Figure 71. `cluster centroidlinkage` performance plot.
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Figure 75. *cluster kmedians* performance plot.
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Figure 78. cluster wardslinkage performance plot.

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Figure 84. `compress` performance plot.

Figure 85. `contract` performance plot.

Figure 86. `corr2data` performance plot.

Figure 87. `correlate` performance plot.
Figure 88. `corrgram` performance plot.

Figure 89. `count` performance plot.

Figure 90. `c poisson` performance plot.

Figure 91. `cs` performance plot.
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Figure 491. `xtdata, fe` performance plot.
Figure 492. xtdata, re performance plot.

Figure 493. xtdpd performance plot.

Figure 494. xtdpdsys performance plot.

Figure 495. xtfrontier performance plot.
Figure 496. `xtgee, family(gaussian) corr(ar2)` performance plot.

Figure 497. `xtgee, fam(gauss) corr(unstruct)` performance plot.

Figure 498. `xtcloglog, pa` performance plot.

Figure 499. `xtlogit, pa` performance plot.
Figure 500. `xtnbreg, pa` performance plot.

Figure 501. `xtpoisson, pa` performance plot.

Figure 502. `xtprobit, pa` performance plot.

Figure 503. `xtreg, pa` performance plot.
Figure 504. *xtgls* performance plot.

Figure 505. *xhtaylor* performance plot.

Figure 506. *xtile* performance plot.

Figure 507. *xtintreg* performance plot.
Figure 508. `xtivreg, be` performance plot.

Figure 509. `xtivreg, fd` performance plot.

Figure 510. `xtivreg, fe` performance plot.

Figure 511. `xtivreg, re` performance plot.
Figure 512. `xtlogit, fe` performance plot.

Figure 513. `xtlogit, re` performance plot.

Figure 514. `xtnbreg, fe` performance plot.

Figure 515. `xtnbreg, re` performance plot.
Figure 516. `xtologit` performance plot.

Figure 517. `xtoprobit` performance plot.

Figure 518. `xtpcse` performance plot.

Figure 519. `xtpcse, corr(ar1)` performance plot.
Figure 520. `xtcse, corr(psar1)` performance plot.

Figure 521. `xtpoisson, fe` performance plot.

Figure 522. `xtpoisson, re` performance plot.

Figure 523. `xtprobit, re` performance plot.
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Figure 524. `xtreg` performance plot.

Figure 525. `xtreg, be` performance plot.

Figure 526. `xtreg, fe` performance plot.

Figure 527. `xtreg, fe vce(robust)` performance plot.
Figure 528. `xtreg, mle` performance plot.

Figure 529. `xtreg, re` performance plot.

Figure 530. `xtregar, fe` performance plot.

Figure 531. `xtregar, re` performance plot.
Figure 532. *xtset* performance plot.

Figure 533. *xtstreg*,
*distribution(exponential)* performance plot.

Figure 534. *xtstreg*,
*distribution(weibull)* performance plot.

Figure 535. *xtsum* performance plot.
Figure 536. *xttab* performance plot.

Figure 537. *xttobit* performance plot.

Figure 538. *xtunitroot breitung* performance plot.

Figure 539. *xtunitroot fisher* performance plot.
Figure 540. *xtunitroot* hadri performance plot.

Figure 541. *xtunitroot* ht performance plot.

Figure 542. *xtunitroot* ips performance plot.

Figure 543. *xtunitroot* llc performance plot.
Figure 544. *zinb* performance plot.

Figure 545. *zip* performance plot.

Figure 546. *predict, xb* performance plot.

Figure 547. *rmcoll* performance plot.
Figure 548. _robust_ performance plot.
B Performance assessment graphs for high-end servers

Performance graphs of all 529 commands running on high-end servers are presented below. These graphs are similar to the graphs from appendix A except that here the speeds are evaluated up to 40 cores.
Figure 549. **Parallelization performance plots.**
Figure 550. Parallelization performance plots.
Figure 551. Parallelization performance plots.
Figure 552. Parallelization performance plots.
Figure 553. Parallelization performance plots.
Figure 554. Parallelization performance plots.
Figure 555. Parallelization performance plots.
Figure 556. Parallelization performance plots.
Figure 557. Parallelization performance plots.
Figure 558. Parallelization performance plots.
Figure 559. Parallelization performance plots.
Figure 560. Parallelization performance plots.
Figure 561. Parallelization performance plots.
Figure 562. Parallelization performance plots.
Figure 563. **Parallelization performance plots.**
Figure 564. Parallelization performance plots.
Figure 565. Parallelization performance plots.
Figure 566. Parallelization performance plots.
Figure 567. Parallelization performance plots.
Figure 568. Parallelization performance plots.
Figure 569. Parallelization performance plots.
<table>
<thead>
<tr>
<th>Function</th>
<th>Plot Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>manova (one-way)</td>
<td>Speed relative to single core for one-way MANOVA.</td>
</tr>
<tr>
<td>manova (two-way)</td>
<td>Speed relative to single core for two-way MANOVA.</td>
</tr>
<tr>
<td>margins</td>
<td>Speed relative to single core for marginal effects.</td>
</tr>
<tr>
<td>margins, dydx()</td>
<td>Speed relative to single core for dydx().</td>
</tr>
<tr>
<td>margins, dydx() exp()</td>
<td>Speed relative to single core for dydx() with exponential transformation.</td>
</tr>
<tr>
<td>margins, exp()</td>
<td>Speed relative to single core for marginal effects with exponential transformation.</td>
</tr>
<tr>
<td>markout</td>
<td>Speed relative to single core for markout.</td>
</tr>
<tr>
<td>marksample</td>
<td>Speed relative to single core for marksample.</td>
</tr>
<tr>
<td>marksample if exp</td>
<td>Speed relative to single core for marksample if exp.</td>
</tr>
</tbody>
</table>

Figure 570. **Parallelization performance plots.**
Figure 571. Parallelization performance plots.
### Parallelization performance plots

<table>
<thead>
<tr>
<th>Function</th>
<th>Speed relative to single core</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Observed</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Fitted</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Perfect scaling</strong></td>
<td></td>
</tr>
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</table>

**Observed**

<table>
<thead>
<tr>
<th>Function</th>
<th>Number of cores</th>
</tr>
</thead>
<tbody>
<tr>
<td>mdslong</td>
<td>1 2 4 8 16 32</td>
</tr>
<tr>
<td>mean</td>
<td>1 2 4 8 16 32</td>
</tr>
<tr>
<td>mecloglog</td>
<td>1 2 4 8 16 32</td>
</tr>
<tr>
<td>median</td>
<td>1 2 4 8 16 32</td>
</tr>
<tr>
<td>melogit</td>
<td>1 2 4 8 16 32</td>
</tr>
<tr>
<td>membreg, dispersion(constant)</td>
<td>1 2 4 8 16 32</td>
</tr>
<tr>
<td>membreg, dispersion(mean)</td>
<td>1 2 4 8 16 32</td>
</tr>
<tr>
<td>meologit</td>
<td>1 2 4 8 16 32</td>
</tr>
<tr>
<td>meoprobit</td>
<td>1 2 4 8 16 32</td>
</tr>
</tbody>
</table>

**Figure 572.** Parallelization performance plots.
Figure 573. Parallelization performance plots.
Figure 574. Parallelization performance plots.
Figure 575. Parallelization performance plots.
Figure 576. Parallelization performance plots.
Figure 577. Parallelization performance plots.
Figure 578. Parallelization performance plots.
Figure 579. Parallelization performance plots.
Figure 580. Parallelization performance plots.
Figure 581. Parallelization performance plots.
Figure 582. Parallelization performance plots.
Figure 583. Parallelization performance plots.
Figure 584. Parallelization performance plots.
Figure 585. Parallelization performance plots.
Figure 586. Parallelization performance plots.
Figure 587. Parallelization performance plots.
Figure 588. Parallelization performance plots.
Figure 589. Parallelization performance plots.
Figure 590. Parallelization performance plots.
Figure 591. Parallelization performance plots.
<table>
<thead>
<tr>
<th>Command</th>
<th>Number of cores</th>
<th>Speed relative to single core</th>
</tr>
</thead>
<tbody>
<tr>
<td>stset</td>
<td>1 2 4 8 16 32</td>
<td></td>
</tr>
<tr>
<td>stsplit</td>
<td>1 2 4 8 16 32</td>
<td></td>
</tr>
<tr>
<td>stsum</td>
<td>1 2 4 8 16 32</td>
<td></td>
</tr>
<tr>
<td>stteffects ipw (weibull)</td>
<td>1 2 4 8 16 32</td>
<td></td>
</tr>
<tr>
<td>stteffects ipwra (weibull)</td>
<td>1 2 4 8 16 32</td>
<td></td>
</tr>
<tr>
<td>stteffects ra (weibull)</td>
<td>1 2 4 8 16 32</td>
<td></td>
</tr>
<tr>
<td>stteffects wra (weibull)</td>
<td>1 2 4 8 16 32</td>
<td></td>
</tr>
<tr>
<td>stvary</td>
<td>1 2 4 8 16 32</td>
<td></td>
</tr>
<tr>
<td>suest</td>
<td>1 2 4 8 16 32</td>
<td></td>
</tr>
</tbody>
</table>

Figure 592. **Parallelization performance plots.**
summarize  sunflower  sureg

svar  svmat  svy brr: logit

svy brr: poisson  svy brr: regress  svy jackknife: logit

Observed  Fitted  Perfect scaling

Speed relative to single core

Number of cores

Figure 593. Parallelization performance plots.
Figure 594. Parallelization performance plots.
Figure 595. Parallelization performance plots.
Figure 596. Parallelization performance plots.
Figure 597. Parallelization performance plots.
Figure 598. **Parallelization performance plots.**
Figure 599. Parallelization performance plots.
Figure 600. Parallelization performance plots.
Figure 601. Parallelization performance plots.
Figure 602. Parallelization performance plots.
Figure 603. Parallelization performance plots.
Figure 604. Parallelization performance plots.
Figure 605. Parallelization performance plots.
Figure 606. **Parallelization performance plots.**
Figure 607. Parallelization performance plots.
## Command names and descriptions

Table 2. Command descriptions

<table>
<thead>
<tr>
<th>Command</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>alpha</td>
<td>Cronbach’s alpha</td>
</tr>
<tr>
<td>ameans</td>
<td>Arithmetic, geometric, and harmonic means</td>
</tr>
<tr>
<td>anova</td>
<td>Analysis of variance and covariance—one-way</td>
</tr>
<tr>
<td>anova</td>
<td>Analysis of variance and covariance—two-way</td>
</tr>
<tr>
<td>arch</td>
<td>Autoregressive conditional heteroskedasticity (ARCH) family of estimators</td>
</tr>
<tr>
<td>areg</td>
<td>Linear regression with a large dummy-variable set</td>
</tr>
<tr>
<td>areg, vce(cluster)</td>
<td>Linear regression with a large dummy-variable set, cluster–robust standard errors</td>
</tr>
<tr>
<td>areg, vce(robust)</td>
<td>Linear regression with a large dummy-variable set, robust (Huber/White) standard errors</td>
</tr>
<tr>
<td>arfima</td>
<td>Autoregressive fractionally integrated moving-average models</td>
</tr>
<tr>
<td>arima</td>
<td>ARIMA, ARMAX, and other dynamic regression models</td>
</tr>
<tr>
<td>asclogit</td>
<td>Alternative-specific conditional logit (McFadden’s choice) model</td>
</tr>
<tr>
<td>asmprobit</td>
<td>Maximum simulated-likelihood alternative-specific multinomial probit models</td>
</tr>
<tr>
<td>asroprobit</td>
<td>Alternative-specific rank-ordered probit regression</td>
</tr>
<tr>
<td>bayesmh logit</td>
<td>Bayesian logistic regression using Metropolis-Hastings algorithm</td>
</tr>
<tr>
<td>bayesmh mvn</td>
<td>Bayesian multivariate normal regression using Metropolis-Hastings algorithm</td>
</tr>
<tr>
<td>bayesmh mylogit</td>
<td>Bayesian logistic regression using Metropolis-Hastings algorithm (custom evaluator)</td>
</tr>
<tr>
<td>bayesmh nl</td>
<td>Bayesian nonlinear regression using Metropolis-Hastings algorithm</td>
</tr>
<tr>
<td>bayesmh normal</td>
<td>Bayesian linear regression using Metropolis-Hastings algorithm</td>
</tr>
<tr>
<td>bayesmh normal gibbs</td>
<td>Bayesian linear regression using Gibbs sampling</td>
</tr>
<tr>
<td>bayesmh normal re</td>
<td>Bayesian linear regression with random effects using Metropolis-Hasting algorithm</td>
</tr>
<tr>
<td>betareg, link(logit)</td>
<td>Beta regression, logit link</td>
</tr>
<tr>
<td>betareg, link(probit)</td>
<td>Beta regression, probit link</td>
</tr>
<tr>
<td>binreg</td>
<td>Generalized linear models: extensions to the binomial family</td>
</tr>
<tr>
<td>biplot</td>
<td>Biplots</td>
</tr>
<tr>
<td>biprobit</td>
<td>Bivariate probit regression</td>
</tr>
</tbody>
</table>
Table 2. Command descriptions

<table>
<thead>
<tr>
<th>Command</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>biprobit</td>
<td>Seemingly unrelated probit regression</td>
</tr>
<tr>
<td>bitest</td>
<td>Binomial probability test</td>
</tr>
<tr>
<td>blogit</td>
<td>Logistic regression for grouped data</td>
</tr>
<tr>
<td>boxcox</td>
<td>Box–Cox regression models</td>
</tr>
<tr>
<td>bprobit</td>
<td>Probit regression for grouped data</td>
</tr>
<tr>
<td>brier</td>
<td>Brier score decomposition</td>
</tr>
<tr>
<td>bsample</td>
<td>Sampling with replacement</td>
</tr>
<tr>
<td>bstat</td>
<td>Compute and report bootstrap statistics</td>
</tr>
<tr>
<td>by: generate</td>
<td>Create new variables over longitudinal/panel data</td>
</tr>
<tr>
<td>by: generate (small groups)</td>
<td>Create new variables over longitudinal/panel data, small panels</td>
</tr>
<tr>
<td>by: replace</td>
<td>Replace variable values over longitudinal/panel data</td>
</tr>
<tr>
<td>by: replace (small groups)</td>
<td>Replace variable values over longitudinal/panel data, small panels</td>
</tr>
<tr>
<td>ca</td>
<td>Simple correspondence analysis</td>
</tr>
<tr>
<td>candisc</td>
<td>Canonical linear discriminant analysis</td>
</tr>
<tr>
<td>canon</td>
<td>Canonical correlations</td>
</tr>
<tr>
<td>cc</td>
<td>Case–control odds ratio</td>
</tr>
<tr>
<td>by: cc</td>
<td>Case–control odds ratio over groups</td>
</tr>
<tr>
<td>centile</td>
<td>Report centile and confidence interval</td>
</tr>
<tr>
<td>churdle linear</td>
<td>Cragg hurdle regression</td>
</tr>
<tr>
<td>ci means</td>
<td>Confidence intervals for means, normal distribution</td>
</tr>
<tr>
<td>ci means, poisson</td>
<td>Confidence intervals for means, Poisson distribution</td>
</tr>
<tr>
<td>ci proportions</td>
<td>Confidence intervals for proportions</td>
</tr>
<tr>
<td>clogit (k1 to k2 matching)</td>
<td>Conditional (fixed-effects) logistic regression, k1 to k2 matching</td>
</tr>
<tr>
<td>clogit (1 to k matching)</td>
<td>Conditional (fixed-effects) logistic regression, 1 to k matching</td>
</tr>
<tr>
<td>cloglog</td>
<td>Complementary log-log regression</td>
</tr>
<tr>
<td>Command</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------</td>
<td>-------------------------------------------------------</td>
</tr>
<tr>
<td><code>cluster averagelinkage</code></td>
<td>Hierarchical cluster analysis—average linkage</td>
</tr>
<tr>
<td><code>cluster centroidlinkage</code></td>
<td>Hierarchical cluster analysis—centroid linkage</td>
</tr>
<tr>
<td><code>cluster completelinkage</code></td>
<td>Hierarchical cluster analysis—complete linkage</td>
</tr>
<tr>
<td><code>cluster generate</code></td>
<td>Generate summary and grouping variables from a cluster analysis</td>
</tr>
<tr>
<td><code>cluster kmeans</code></td>
<td>Kmeans cluster analysis</td>
</tr>
<tr>
<td><code>cluster kmedians</code></td>
<td>Kmedians cluster analysis</td>
</tr>
<tr>
<td><code>cluster medianlinkage</code></td>
<td>Hierarchical cluster analysis—median linkage</td>
</tr>
<tr>
<td><code>cluster singlelinkage</code></td>
<td>Hierarchical cluster analysis—single linkage</td>
</tr>
<tr>
<td><code>cluster wardslinage</code></td>
<td>Hierarchical cluster analysis—Ward’s linkage</td>
</tr>
<tr>
<td><code>cluster waveralglinkage</code></td>
<td>Hierarchical cluster analysis—Ward’s average linkage</td>
</tr>
<tr>
<td><code>cnsreg</code></td>
<td>Constrained linear regression</td>
</tr>
<tr>
<td><code>codebook</code></td>
<td>Describe data contents</td>
</tr>
<tr>
<td><code>collapse</code></td>
<td>Make dataset of summary datasets</td>
</tr>
<tr>
<td><code>compare</code></td>
<td>Compare two variables</td>
</tr>
<tr>
<td><code>compress</code></td>
<td>Compress data in memory</td>
</tr>
<tr>
<td><code>contract</code></td>
<td>Make dataset of frequencies and percentages</td>
</tr>
<tr>
<td><code>corr2data</code></td>
<td>Create dataset with specified correlation structure</td>
</tr>
<tr>
<td><code>correlate</code></td>
<td>Correlations (covariances) of variables or estimators</td>
</tr>
<tr>
<td><code>corrgram</code></td>
<td>Tabulate and graph autocorrelations</td>
</tr>
<tr>
<td><code>count</code></td>
<td>Count observations satisfying specified condition</td>
</tr>
<tr>
<td><code>cpoisson</code></td>
<td>Censored Poisson regression</td>
</tr>
<tr>
<td><code>cs</code></td>
<td>Cohort study risk-ratio</td>
</tr>
<tr>
<td><code>by: cs</code></td>
<td>Cohort study risk-ratio over groups</td>
</tr>
<tr>
<td><code>ctset</code></td>
<td>Declare data to be count-time data</td>
</tr>
<tr>
<td><code>cttost</code></td>
<td>Convert count-time data to survival-time data</td>
</tr>
<tr>
<td>Command</td>
<td>Description</td>
</tr>
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<td>-----------------</td>
<td>--------------------------------------------------</td>
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<tr>
<td>cumul</td>
<td>Cumulative distribution</td>
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<tr>
<td>cusum</td>
<td>Cusum plots and tests for binary variables</td>
</tr>
<tr>
<td>datasignature</td>
<td>Determine whether data have changed</td>
</tr>
<tr>
<td>decode</td>
<td>Decode labeled numeric into string</td>
</tr>
<tr>
<td>destring</td>
<td>Convert string variables to numeric variables</td>
</tr>
<tr>
<td>dfactor</td>
<td>Dynamic-factor models</td>
</tr>
<tr>
<td>dfgls</td>
<td>DF-GLS unit-root test</td>
</tr>
<tr>
<td>dfuller</td>
<td>Augmented Dickey–Fuller unit-root test</td>
</tr>
<tr>
<td>discrim knn</td>
<td>Discriminant analysis—$k$th-nearest-neighbor</td>
</tr>
<tr>
<td>discrim lda</td>
<td>Discriminant analysis—linear</td>
</tr>
<tr>
<td>discrim logistic</td>
<td>Discriminant analysis—logistic</td>
</tr>
<tr>
<td>discrim qda</td>
<td>Discriminant analysis—quadratic</td>
</tr>
<tr>
<td>dotplot</td>
<td>Comparative scatterplots</td>
</tr>
<tr>
<td>drawnorm</td>
<td>Draw sample from multivariate normal distribution</td>
</tr>
<tr>
<td>drop if $exp$</td>
<td>Eliminate observations using if expression</td>
</tr>
<tr>
<td>drop in $range$</td>
<td>Eliminate observations using in range</td>
</tr>
<tr>
<td>dstdize</td>
<td>Direct and indirect standardization</td>
</tr>
<tr>
<td>dvech</td>
<td>Diagonal vech multivariate GARCH models</td>
</tr>
<tr>
<td>egen group()</td>
<td>Extensions to generate—create grouping variable</td>
</tr>
<tr>
<td>by: egen mean</td>
<td>Extensions to generate—create means over groups</td>
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<td>eivreg</td>
<td>Errors-in-variables regression</td>
</tr>
<tr>
<td>encode</td>
<td>Encode string into numeric</td>
</tr>
<tr>
<td>esize twosample</td>
<td>Effect size for two independent samples using groups</td>
</tr>
<tr>
<td>esize unpaired</td>
<td>Effect size for two independent samples using variables</td>
</tr>
<tr>
<td>eteffects (exponential), ate</td>
<td>Endogenous treatment-effects estimation, exponential-mean model, average treatment effect in population</td>
</tr>
<tr>
<td>Command</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>eteffects (linear), ate</td>
<td>Endogenous treatment-effects estimation, linear model, average treatment</td>
</tr>
<tr>
<td>eteffects (linear), pmeans</td>
<td>Endogenous treatment-effects estimation, linear model, potential-outcome</td>
</tr>
<tr>
<td>eteffects (probit), ate</td>
<td>Endogenous treatment-effects estimation, probit model, average treatment</td>
</tr>
<tr>
<td>etpoisson</td>
<td>Poisson regression with endogenous treatment effects</td>
</tr>
<tr>
<td>etregress, poutcomes</td>
<td>Linear regression with endogenous treatment effects, ML estimation with</td>
</tr>
<tr>
<td>etregress, twostep</td>
<td>Linear regression with endogenous treatment effects, two-step estimation</td>
</tr>
<tr>
<td>exlogistic</td>
<td>Exact logistic regression</td>
</tr>
<tr>
<td>expand #</td>
<td>Duplicate observations</td>
</tr>
<tr>
<td>expand varname</td>
<td>Duplicate observations using a variable</td>
</tr>
<tr>
<td>expandcl #</td>
<td>Duplicate clustered observations</td>
</tr>
<tr>
<td>expandcl varname</td>
<td>Duplicate clustered observations using a variable</td>
</tr>
<tr>
<td>expoisson</td>
<td>Exact Poisson regression</td>
</tr>
<tr>
<td>factor</td>
<td>Factor analysis</td>
</tr>
<tr>
<td>fcast compute</td>
<td>Dynamic forecasts after VAR or VEC estimation</td>
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<tr>
<td>fillin</td>
<td>Rectangularize dataset</td>
</tr>
<tr>
<td>fracreg probit</td>
<td>Fractional probit regression</td>
</tr>
<tr>
<td>frontier</td>
<td>Stochastic frontier models</td>
</tr>
<tr>
<td>fvrevar (factors)</td>
<td>Create indicators for factor variables</td>
</tr>
<tr>
<td>fvrevar (interaction)</td>
<td>Create indicators for factor variables—interactions</td>
</tr>
<tr>
<td>generate (small expressions)</td>
<td>Create or change contents of variable—small expressions</td>
</tr>
<tr>
<td>generate</td>
<td>Create or change contents of variable</td>
</tr>
<tr>
<td>glm, family(gamma)</td>
<td>Generalized linear models—gamma distribution</td>
</tr>
<tr>
<td>glm, family(gaussian)</td>
<td>Generalized linear models—Gaussian distribution</td>
</tr>
<tr>
<td>glm, family(igaussian)</td>
<td>Generalized linear models—inverse Gaussian distribution</td>
</tr>
<tr>
<td>glm, family(nbinomial)</td>
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Table 2. Command descriptions

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<td>glogit</td>
<td>Weighted least-squares logistic regression for grouped data</td>
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<td>gmm</td>
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<td>gmm (with derivatives)</td>
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<td>gprobit</td>
<td>Weighted least-squares probit regression for grouped data</td>
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<tr>
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<td>mi estimate: logit (flong)</td>
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<td>mi impute chained (flongsep)</td>
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<td>Procrustes transformation</td>
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<td>proportion</td>
<td>Estimate proportions</td>
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<tr>
<td>prtest1</td>
<td>One-sample tests of proportions</td>
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<td>prtest2</td>
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<td>prtest, by()</td>
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<tr>
<td>pwcorr</td>
<td>Pairwise correlation coefficients</td>
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<tr>
<td>qreg</td>
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<tr>
<td>ranksum</td>
<td>Equality tests on unmatched data</td>
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<tr>
<td>ratio</td>
<td>Estimate ratio with SE and CI</td>
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<tr>
<td>ratio (exp1) (exp2)</td>
<td>Estimate two ratios with SE and CI</td>
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<td>recode</td>
<td>Recode categorical variables</td>
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<td>reg3</td>
<td>Three-stage estimation for systems of simultaneous equations</td>
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<tr>
<td>regress</td>
<td>Linear regression</td>
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<td>regress, vce(cluster)</td>
<td>Linear regression, cluster-robust standard errors</td>
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<tr>
<td>regress, vce(robust)</td>
<td>Linear regression, robust (Huber/White) standard errors</td>
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<tr>
<td>replace</td>
<td>Create or change contents of variable</td>
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<tr>
<td>replace (small expressions)</td>
<td>Create or change contents of variable, simple expression</td>
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<tr>
<td>reshape long</td>
<td>Convert data from wide to long</td>
</tr>
<tr>
<td>reshape wide</td>
<td>Convert data from long to wide</td>
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<tr>
<td>robvar</td>
<td>Robust tests for equality of variance</td>
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<tr>
<td>rocfit</td>
<td>Fit ROC models</td>
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<td>roctab</td>
<td>Receiver operating characteristic (ROC) analysis</td>
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<td>rotate</td>
<td>Orthogonal and oblique rotations after factor and pca</td>
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<td>rotatemat</td>
<td>Orthogonal and oblique rotations of a Stata matrix</td>
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<td>rreg</td>
<td>Robust regression</td>
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<td>runtest</td>
<td>Test for random order</td>
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<td>scobit</td>
<td>Skewed logistic regression</td>
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<td>scoreplot</td>
<td>Score and loading plots after factor and pca</td>
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<td>screeplot</td>
<td>Scree plot of eigenvalues</td>
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<td>sdtest1</td>
<td>Variance-comparison test against constant</td>
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<td>sdtest2</td>
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<td>sdtest, by()</td>
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<td>sem, method(ADF) (CFA)</td>
<td>Confirmatory factor analysis, ADF estimation</td>
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<td>sem, method(ml) (CFA)</td>
<td>Confirmatory factor analysis, ML estimation</td>
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<td>sem, method(mlmv) (CFA)</td>
<td>Confirmatory factor analysis, ML estimation with missing values</td>
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<td>Command</td>
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<td><code>sem (SEM latent)</code></td>
<td>Structural equations model with latent variables, ML estimation</td>
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<td><code>sem (SEM observed)</code></td>
<td>Structural equations model on observed variables, ML estimation</td>
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<td><code>separate</code></td>
<td>Create separate variables</td>
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<td><code>sfrancia</code></td>
<td>Shapiro–Francia test for normality</td>
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<tr>
<td><code>signrank</code></td>
<td>Equality tests on matched data</td>
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<tr>
<td><code>signtest</code></td>
<td>Equality tests on matched data</td>
</tr>
<tr>
<td><code>sktest</code></td>
<td>Skewness and kurtosis test for normality</td>
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<td><code>slogit</code></td>
<td>Stereotype logistic regression</td>
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<tr>
<td><code>sort</code></td>
<td>Sort data</td>
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<td><code>spearman</code></td>
<td>Spearman’s rank correlation coefficients</td>
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<td><code>sspace</code></td>
<td>State-space models</td>
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<td><code>stack</code></td>
<td>Stack data</td>
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<tr>
<td><code>stci</code></td>
<td>Confidence intervals for means and percentiles of survival time</td>
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<tr>
<td><code>stcox</code></td>
<td>Fit Cox proportional hazards model</td>
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<td><code>stcrreg</code></td>
<td>Competing-risks regression</td>
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<tr>
<td><code>stgen</code></td>
<td>Generate variables reflecting entire histories</td>
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<td><code>stir</code></td>
<td>Report incidence-rate comparison</td>
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<tr>
<td><code>stmc</code></td>
<td>Calculate rate ratios with the Mantel–Cox method</td>
</tr>
<tr>
<td><code>by: stmc</code></td>
<td>Calculate rate ratios with the Mantel–Cox method over groups</td>
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<tr>
<td><code>stmh</code></td>
<td>Calculate rate ratios with the Mantel–Haenszel method</td>
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<tr>
<td><code>by: stmh</code></td>
<td>Calculate rate ratios with the Mantel–Haenszel method over groups</td>
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<tr>
<td><code>stptime</code></td>
<td>Calculate person-time, incidence rates, and SMR</td>
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<tr>
<td><code>strate</code></td>
<td>Tabulate failure rates and rate ratios</td>
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<tr>
<td><code>streg,</code></td>
<td>Fit parametric survival models, exponential distribution</td>
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<tr>
<td><code>distribution(exponential)</code></td>
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<td><code>streg, dist(exp)</code></td>
<td>Fit parametric survival models, exponential distribution with cluster–</td>
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<tr>
<td><code>vce(cluster)</code></td>
<td>robust standard errors</td>
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<td><code>streg, dist(exp)</code></td>
<td>Fit parametric survival models, exponential distribution with individual frailty</td>
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<tr>
<td><code>frailty()</code></td>
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</tr>
<tr>
<td><code>streg, dist(exp)</code></td>
<td>Fit parametric survival models, exponential distribution with shared frailty</td>
</tr>
<tr>
<td><code>frailty()</code></td>
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</tr>
<tr>
<td><code>streg, dist(exp)</code></td>
<td>Fit parametric survival models, exponential distribution with robust standard errors</td>
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<tr>
<td><code>vce(robust)</code></td>
<td></td>
</tr>
<tr>
<td><code>streg, distribution(gamma)</code></td>
<td>Fit parametric survival models, gamma distribution</td>
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<tr>
<td><code>streg, distribution(lnormal)</code></td>
<td>Fit parametric survival models, log-normal distribution</td>
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<tr>
<td><code>streg, distribution(weibull)</code></td>
<td>Fit parametric survival models, Weibull distribution</td>
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<tr>
<td><code>sts generate</code></td>
<td>Create new variables containing survival, hazard, and related functions</td>
</tr>
<tr>
<td><code>sts graph</code></td>
<td>Compute and graph survival, hazard, and related functions</td>
</tr>
<tr>
<td><code>sts list</code></td>
<td>Compute and list survival and related functions</td>
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<tr>
<td><code>sts test</code></td>
<td>Test the equality of the survival function across groups</td>
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<td><code>stset</code></td>
<td>Declare data to be survival-time data</td>
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<tr>
<td><code>stsplit</code></td>
<td>Split time-span records</td>
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<tr>
<td><code>stsum</code></td>
<td>Summarize survival-time data</td>
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<tr>
<td><code>stteffects ipw (weibull)</code></td>
<td>Treatment-effects estimation for survival data, inverse-probability weighting, Weibull distribution</td>
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<tr>
<td><code>stteffects ipwra (weibull)</code></td>
<td>Treatment-effects estimation for survival data, inverse-probability weighted regression adjustment, Weibull distribution</td>
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<tr>
<td><code>stteffects ra (weibull)</code></td>
<td>Treatment-effects estimation for survival data, regression adjustment, Weibull distribution</td>
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<tr>
<td><code>stteffects wra (weibull)</code></td>
<td>Treatment-effects estimation for survival data, weighted regression adjustment, Weibull distribution</td>
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<tr>
<td><code>stvary</code></td>
<td>Report variables that vary over time</td>
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<td><code>suest</code></td>
<td>Seemingly unrelated estimation</td>
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<td><code>summarize</code></td>
<td>Summary statistics</td>
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<td><code>sunflower</code></td>
<td>Density-distribution sunflower plots</td>
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<td><code>sureg</code></td>
<td>Zellner’s seemingly unrelated regression</td>
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<tr>
<td><code>svar</code></td>
<td>Structural vector autoregression models</td>
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<tr>
<td>Command</td>
<td>Description</td>
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<tr>
<td>svmat</td>
<td>Convert variables to matrix and vice versa</td>
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<td>svy brr: logit</td>
<td>Logistic regression using survey data—balanced repeated replications</td>
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<tr>
<td>svy brr: poisson</td>
<td>Poisson regression using survey data—balanced repeated replications</td>
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<tr>
<td>svy brr: regress</td>
<td>Linear regression using survey data—balanced repeated replications</td>
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<td>svy jackknife: logit</td>
<td>Logistic regression using survey data—jackknife</td>
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<tr>
<td>svy jackknife: poisson</td>
<td>Poisson regression using survey data—jackknife</td>
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<tr>
<td>svy jackknife: regress</td>
<td>Linear regression using survey data—jackknife</td>
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<td>svy linearized: logit</td>
<td>Logistic/logit regression using survey data—linearization</td>
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<td>svy linearized: poisson</td>
<td>Poisson regression using count survey data—linearization</td>
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<td>svy linearized: regress</td>
<td>Linear regression using survey data—linearization</td>
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<td>swilk</td>
<td>Shapiro–Wilk test for normality</td>
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<td>symmetry</td>
<td>Symmetry and marginal homogeneity tests</td>
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<td>table (one-way)</td>
<td>Table of summary statistics, one-way</td>
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<tr>
<td>table (two-way)</td>
<td>Table of summary statistics, two-way</td>
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<td>tabodds</td>
<td>Tabulate odds of failure by category</td>
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<tr>
<td>tabodds (adjusted)</td>
<td>Tabulate odds of failure by category adjusting for levels</td>
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<tr>
<td>tabstat</td>
<td>Display table of summary statistics</td>
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<tr>
<td>tabstat, by()</td>
<td>Display table of summary statistics over groups</td>
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<td>tabulate (one-way)</td>
<td>Tables of frequencies, one-way</td>
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<tr>
<td>tabulate (two-way)</td>
<td>Tables of frequencies, two-way</td>
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<td>teffects aipw (linear)</td>
<td>Treatment-effects estimation for linear regression, augmented inverse-probability weighting</td>
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<td>teffects aipw (probit)</td>
<td>Treatment-effects estimation for probit regression, augmented inverse-probability weighting</td>
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<td>teffects ipw (logit)</td>
<td>Treatment-effects estimation for linear regression, inverse-probability weighting</td>
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<tr>
<td>teffects ipwra (linear)</td>
<td>Treatment-effects estimation for linear regression, inverse-probability weight regression adjustment</td>
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<tr>
<td>teffects ipwra (probit)</td>
<td>Treatment-effects estimation for probit regression, augmented inverse-probability weighted regression adjustment</td>
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<tr>
<td>Command</td>
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<td>teffects nnmatch</td>
<td>Treatment-effects estimation, nearest-neighbor matching</td>
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<td>teffects psmatch, logit</td>
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<td>teffects ra (linear)</td>
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<td>teffects ra (probit)</td>
<td>Treatment-effects estimation for probit regression, regression adjustment</td>
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<td>tetrachoric</td>
<td>Tetrachoric correlations for binary variables</td>
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<td>Truncated negative binomial regression</td>
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<td>Tobit regression</td>
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<td>tostring</td>
<td>Convert numeric variables to string variables</td>
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<td>total</td>
<td>Estimate totals</td>
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<td>Truncated Poisson regression</td>
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<td>truncreg</td>
<td>Truncated regression</td>
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<td>tsfilter bk</td>
<td>Time-series filter, Baxter-King</td>
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<td>tsfilter bw</td>
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<td>tsfilter cf</td>
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<td>tsfilter hp</td>
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<td>tsset</td>
<td>Declare a dataset to be time-series data</td>
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<td>tssMOOTH exp</td>
<td>Exponential smoothing of univariate time-series data</td>
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<td>tssMOOTH ma</td>
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<td>twoway fpfit</td>
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<tr>
<td>twoway lfitci</td>
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<td>twoway mband</td>
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<td>Compute and graph spline smooth</td>
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<td>ucm, model(rwdrift)</td>
<td>Unobserved-components model, random walk with drift</td>
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<td>var</td>
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<td>vargranger</td>
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<td>varlmar</td>
<td>Obtain LM statistics for residual autocorrelation after var or svar</td>
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<td>varnorm</td>
<td>Test for normally distributed disturbances after var or svar</td>
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<td>varsoc</td>
<td>Obtain lag-order selection statistics for VARs and VECMs</td>
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<td>vecrank</td>
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<td>Arellano–Bond linear, dynamic panel-data estimation</td>
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<td>Arellano–Bond linear, dynamic panel-data estimation, two-step estimation</td>
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<td>Random-effects cloglog models</td>
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<td>xtdata, fe</td>
<td>Compute within (fixed-effects) transform of panel data</td>
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<td>xtdata, re</td>
<td>Compute random-effects transform of panel data</td>
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<td>xtdpd</td>
<td>Linear dynamic panel-data estimation</td>
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<td>xtdpdsys</td>
<td>Arellano–Bover/Blundell–Bond linear dynamic panel-data estimation</td>
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<td>xtfrontier</td>
<td>Stochastic frontier models for panel data</td>
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<td>xtgee, family(gaussian)</td>
<td>GEE estimation of Gaussian panel-data model with 2-period autocorrelation</td>
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<td>xtgee, fam(gauss)</td>
<td>GEE estimation of Gaussian panel-data model with unstructured correlation</td>
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<td>Population-averaged cloglog models</td>
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<td>Population-averaged logit models</td>
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<td>Population-averaged Poisson models</td>
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<td>Random-effects interval data regression models</td>
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<td>Panel-data line plots</td>
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<td>xtprobit</td>
<td>Random-effects ordered probit models</td>
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<td>xtpcse</td>
<td>OLS or Prais–Winsten models with panel-corrected standard errors</td>
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<td>Prais–Winsten models with panel-corrected standard errors</td>
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<td>Prais–Winsten models with panel-corrected standard errors—panel-specific autocorrelation</td>
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<td>Fixed-effects Poisson models</td>
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<td>Random-effects Poisson models</td>
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<td><code>xtprobit, re</code></td>
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<td><code>xtreg, fe</code></td>
<td>Fixed-effects linear models</td>
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<tr>
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D Problem sizes

The following table (table 3) shows the sizes of the problems used to measure the performance gains reported in table 1. As discussed in section 9, these are intentionally large problems requiring considerable time to run. If a command was so fast that a sufficiently large problem would have required too much memory to be run on a variety of computers, then a smaller problem was run several times (several iterations) for an accurate read of the timing required to run the command.

The second through fourth columns of table 3 record the number of observations for the problem, either as a simple number of observations $N$ or as a number of panels $m$ and a number of time periods $t$ within a panel. Columns 3 and 4 provide more information on problem size for longitudinal panel-data problems, and the number of observations, $N$, is just the product of $m$ and $t$. Some such problems are not really panel data but merely grouped data; in these cases, the time periods should just be considered the number of observations within group. Almost all the panel-data problems were created with balanced panels (an equal number of observations within panel). Rarely would unbalanced panels affect the performance gains of Stata/MP.

The column labeled $k$ records the number of covariates in the problem or, for matrix commands, the row and column dimensions of the matrix.

The column labeled $n_{eq}$ records the number of equations for problems that involve multiple equations.

The column labeled $n_{iter}$ records the number of times the command was run on the problem to generate a single timing.
## Table 3. Problem sizes

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N, number of observations; m, number of panels; t, number of time periods within each panel; k, number of regressors; n_{eq}, number of equations; and n_{iter}, number of iterations.

See appendix C for command descriptions.
Table 3. Problem sizes

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N, number of observations; m, number of panels; t, number of time periods within each panel; k, number of regressors; neq, number of equations; and niter, number of iterations.

See appendix C for command descriptions.
Table 3. Problem sizes

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N, number of observations; m, number of panels; t, number of time periods within each panel; k, number of regressors; neq, number of equations; and niter, number of iterations.
## Table 3. Problem sizes

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N, number of observations; m, number of panels; t, number of time periods within each panel; k, number of regressors; neq, number of equations; and niter, number of iterations.
## Table 3. Problem sizes

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$N$, number of observations; $m$, number of panels; $t$, number of time periods within each panel; $k$, number of regressors; $n_{eq}$, number of equations; and $n_{iter}$, number of iterations.

See appendix C for command descriptions.
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<td>xtunitroot ht</td>
<td>300</td>
<td>2000</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>xtunitroot ips</td>
<td>1000</td>
<td>20</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>xtunitroot llc</td>
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<td>500</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>zinb</td>
<td>150000</td>
<td>50</td>
<td>50</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

$N$, number of observations; $m$, number of panels; $t$, number of time periods within each panel; $k$, number of regressors; $n_{eq}$, number of equations; and $n_{iter}$, number of iterations.

See appendix C for command descriptions.
Table 3. Problem sizes

<table>
<thead>
<tr>
<th>Command</th>
<th>Observations</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>zip</td>
<td>250000</td>
<td>50</td>
<td>50</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>_predict, xb</td>
<td>5000000</td>
<td>1000</td>
<td></td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>rmcoll</td>
<td>6000000</td>
<td>100</td>
<td></td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>_robust</td>
<td>3000000</td>
<td>200</td>
<td></td>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$N$, number of observations; $m$, number of panels; $t$, number of time periods within each panel; $k$, number of regressors; $n_{eq}$, number of equations; and $n_{iter}$, number of iterations.
E Commands not assessed

Some commands were not explicitly assessed and thus do not appear in table 1 or in the performance graphs in appendix A. These commands fall into several categories, as detailed below.

Replication-based prefix commands, such as bootstrap, fracpoly, jackknife, mfp, permute, rolling, simulate, statsby, and stepwise, were not explicitly assessed. These commands run another target command repeatedly; to the extent the target command’s performance is improved for a particular problem size, a similar improvement will be obtained when it is run repeatedly by the prefix command.

Commands that do not process data or otherwise involve lengthy computations and are therefore inherently fast are not parallelized and so their performance was not assessed. These commands include camat, clear, clonvar, confirm, describe, estat, estimates, factormat, fvexpand, fvunab, lincom, nlcom, pcamat, roccomp, rocgold, sampsi, search, stpower, svydes, test, testnl, unabbrev, and varabbrev.

Commands that involve file I/O or Internet access are not parallelized and so were not assessed. These include adoupdate, append, cf, fdadescribe, fdasave, fdause, filefilter, hsearch, icd9, icd10, infile, insheet, merge, odbc, outfile, outsheet, rmdir, save, search, snapshot, use, xmlsave, xmluse, zipfile, and unzipfile.

Only a subset of prediction options were assessed. If all predictions were included, they would unduly dominate the timings. Most other predictions have performances similar to the predictions presented in table 1 and in appendix A. Two prediction-like commands whose results are not obtained from predict but whose timings are similar to predict are fracpred and dfbeta.

Some commands are partially parallelized, but their degree of parallelization is extremely variable with respect to the size and characteristics of the data. These commands were not assessed and include bcskew0, lnskew0, fracplot, fracgen, mkmat, stbase, and stjoin.

ac and pac are two time-series commands that are not parallelized and so their performance was not assessed.

graph twoway is not parallelized although a few of its plottypes that involve data management or estimation are parallelized, such as histogram, lowess, lfit, and qfit. Most statistical graphs in Stata are based on graph twoway. Graphs that involve data management or estimation were assessed and appear in table 1 and appendix A. Graphs that do not involve data management or estimation are not parallelized and so their performance was not assessed. These include acprplot, avplot, avplots, cabiplot, caprojection, cchart, cluster tree, cprplot, graph twoway, lvr2plot, mdshepard, pchart, procoverlay, qby, qchi, qnorm, qqplot, quantile, rchart, rocplot, rvfplot, rvpplot, shewhart, spikeplot, stcoxkm, stcurve, stphplot, and symplot.

A number of commands perform similarly to related commands that were assessed, but these commands were not themselves assessed. bsqreg, iqreg, and sqreg perform similarly to qreg. gladder and qladder perform similarly to ladder. gnbreg is similar to nbreg. xttrans is similar to xttab.
**F Mata**

Mata is Stata’s optimized matrix programming language. It is fully integrated with every aspect of Stata. Some parts of Mata are parallelized and some parts are not. As with Stata, you do not need to change anything to obtain the parallelization speedups; they are automatic.

Those parts of Mata that are parallelized are fully parallelized, meaning that on large enough problems, their speedups will be close to the best theoretical speedups discussed in section 6.

The following Mata functions are parallelized: Cofc(), Cofd(), F(), Fden(), Ftail(), acos(), arg(), asin(), atan(), atan2(), betaden(), binomial(), binomialtail(), binormal(), ceil(), chi2(), chi2den(), chi2tail(), cofC(), cofd(), comb(), cos(), cross(), crossdev(), day(), dgammapda(), dgammapdada(), dgammapdadx(), dgammapdx(), dgammpdxdx(), digamma(), dofC(), dofh(), dofm(), dofq(), dofw(), dofy(), dow(), doy(), dunnnettprob(), exp(), exponential(), exponentialden(), exponentialtail(), factorial(), floatround(), floor(), gammaden(), gammap(), gammaparttail(), halfyear(), hh(), hhC(), hofd(), hours(), ibeta(), ibetatail(), invF(), invFtail(), invbinomial(), invbinomialtail(), invchi2(), invchi2tail(), invdunnnettprob(), invexponential(), invexponentialtail(), invgammap(), invgammaparttail(), invibeta(), invibetatail(), invlogistic(), invlogisticpartail(), invnF(), invnFtail(), invnchi2(), invnchi2tail(), invnibeta(), invnnormal(), invnt(), invntail(), invt(), invtail(), invtukeyprob(), invweibull(), invweibullph(), invweibullphden(), invweibullphtail(), invweibullphtailtail(), ln(), lnfactorial(), lngamma(), lngammaden(), lnnormal(), lnnormalden(), logistic(), logisticden(), logistictail(), mdy(), minutes(), mm(), mmC(), mod(), mofd(), month(), msofhours(), msofminutes(), msofseconds(), nF(), nFden(), nFtail(), nbetaden(), nchi2(), nibeta(), normal(), normalden(), npnF(), npnchi2(), npnt(), nt(), ntden(), nttail(), qofd(), quadcross(), quadcrossdev(), quarter(), round(), seconds(), sin(), sqrt(), ss(), st_data(), t(), tan(), tden(), trigamma(), trunc(), ttail(), tukeyprob(), week(), weibull(), weibulden(), weibullph(), weibullphden(), weibullphtail(), weibullphtailtail(), wofd(), year(), yh(), ym(), yq(), and yw.

In addition, matrix multiplication in Mata is fully parallelized, as are Mata’s colon operators for performing elementwise computations. All other parts of Mata are either not parallelized or are functions of a mixture of the two.
G  GLLAMM

Table 4 below shows results for a few models fit using *gllamm*. This is but a small subset of the models that *gllamm* can fit. Each command is described briefly in table 5.

The user-written command *gllamm* (generalized linear latent and mixed models) adds to Stata the ability to fit multilevel, mixed, or hierarchical regression models that have continuous, count, binary, or ordinal dependent variables. In addition, the model may have latent (unobserved) variables, endogenous covariates, and random coefficients or intercepts at any level. Among the many models that *gllamm* can fit, some important special cases include generalized linear mixed models, multilevel regression models, factor models, item response models, structural equation models, latent-class models, generalized linear models with covariate measurement error, endogenous switching and sample selection models, and Rasch models (including multidimensional marginally sufficient Rasch models).

*gllamm*’s authors, Sophia Rabe-Hesketh with contributions from Anders Skrondal and Andrew Pickles, maintain a web site—http://www.gllamm.org/—with complete documentation (140 pages), tutorials, worked examples, wrapper commands to ease estimation of special models, dates of upcoming courses on *gllamm*, and references (often with links) to more than 150 papers published on using *gllamm* to fit models.

*gllamm* uses full maximum likelihood to estimate the parameters of models and uses Gauss–Hermite quadrature or adaptive quadrature to evaluate the integrals of the likelihood. This common computation engine is one reason *gllamm* is so flexible and can fit so many models. It is, however, exceedingly computationally intensive, with the effect that *gllamm* can require substantial time to fit models. *gllamm* users are interested in seeing it run faster.

*gllamm* uses many Stata commands that have been parallelized, and some of *gllamm*’s algorithms, sections of which have been parallelized, are written in C. Even so, *gllamm* incorporates many algorithms, and these algorithms are triggered differently when fitting different models. It is difficult to say anything definitive about performance gains for *gllamm* when run under Stata/MP. Many *gllamm* models are highly parallelized, some not parallelized at all, and others lie somewhere in between.
### Table 4. Stata/MP performance, command by command

<table>
<thead>
<tr>
<th>Command</th>
<th>Number of cores</th>
<th>Percentage parallelized</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Finite mixture model</td>
<td>2.3</td>
<td>3.5</td>
</tr>
<tr>
<td>Item response model</td>
<td>1.4</td>
<td>2.1</td>
</tr>
<tr>
<td>Latent class model</td>
<td>1.3</td>
<td>1.9</td>
</tr>
<tr>
<td>Measurement error model</td>
<td>1.8</td>
<td>2.7</td>
</tr>
<tr>
<td>Rank-outcome latent class</td>
<td>1.8</td>
<td>2.6</td>
</tr>
<tr>
<td>MIMIC model</td>
<td>1.2</td>
<td>1.8</td>
</tr>
<tr>
<td>Random-effects logistic</td>
<td>1.4</td>
<td>2.0</td>
</tr>
<tr>
<td>RE regression</td>
<td>1.5</td>
<td>2.2</td>
</tr>
<tr>
<td>Two-level RE logistic</td>
<td>1.2</td>
<td>1.8</td>
</tr>
<tr>
<td>Random-coefficients Poisson</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>RE logistic with constant</td>
<td>1.6</td>
<td>2.3</td>
</tr>
</tbody>
</table>

All values are expressed as the speed relative to the speed of a single core.

- **a.** Bigger is better; 2 is perfect for 2 cores, 4 is perfect for 4 cores, 8 is perfect for 8 cores, and 16 is perfect for 16 cores.
- **b.** Bigger is better; 100 is perfect.

### Table 5. Command descriptions

<table>
<thead>
<tr>
<th>Command</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finite mixture model</td>
<td>Gaussian finite mixture model with two point masses</td>
</tr>
<tr>
<td>Item response model</td>
<td>Two-parameter logistic item response model</td>
</tr>
<tr>
<td>Latent class model</td>
<td>Gaussian latent class model with two levels in the latent class</td>
</tr>
<tr>
<td>Measurement error model</td>
<td>Logistic regression with measurement error in a covariate</td>
</tr>
<tr>
<td>Rank-outcome latent class</td>
<td>Latent class model for rank outcomes</td>
</tr>
<tr>
<td>MIMIC model</td>
<td>Multiple-indicator, multiple-cause (MIMIC) latent variables structural equation model—ordered logistic</td>
</tr>
<tr>
<td>Random-effects logistic</td>
<td>Random-effects (random-intercepts) logistic regression—same as <code>xtlogit, re</code></td>
</tr>
<tr>
<td>RE regression</td>
<td>Continuous (Gaussian distribution) model with random intercepts—same as <code>xtreg, re</code></td>
</tr>
<tr>
<td>Two-level RE logistic</td>
<td>Logistic regression with two levels of random intercepts</td>
</tr>
<tr>
<td>Random-coefficients Poisson</td>
<td>Poisson count-data model with random intercepts and a random coefficient</td>
</tr>
<tr>
<td>RE logistic with constant</td>
<td>Random-effects (random-intercepts) logistic regression, fewer observations</td>
</tr>
</tbody>
</table>

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The graphs below show the observed performances from table 4 in graphical form. Those graphs are followed by graphs showing performance through 40 cores.
Figure 608. Finite mixture model performance plot.

Figure 609. Item response model performance plot.

Figure 610. Latent class model performance plot.

Figure 611. Measurement error model performance plot.
Figure 612. Rank-outcome latent class performance plot.

Figure 613. MIMIC model performance plot.

Figure 614. Random-effects logistic performance plot.

Figure 615. RE regression performance plot.
Figure 616. Two-level RE logistic performance plot.

Figure 617. Random-coefficients Poisson performance plot.

Figure 618. RE logistic with constant performance plot.
Figure 619. Parallelization performance plots.
Figure 620. Parallelization performance plots.
References


